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Designing Resilient Supply Networks under Disruptions

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Abstract. This paper studies various modeling approaches to design resilient Supply Networks (SN) for the location-transportation problem under uncertainty. The future environment of the SN is assumed to be shaped by random demands, and by hazardous events perturbating depots capacity and ship-to-point demand processes. The paper proposes several anticipation-based stochastic programming models incorporating alternative resilience seeking formulations. A generic approach to generate plausible future scenarios, and to elaborate and evaluate SN designs is also proposed. Experiments are made to compare the SN design models proposed, and recommendations are drawn on the approach to use to design effective and robust supply networks.

Keywords. Supply Network (SN) design, uncertainty, resilience, scenario planning, network disruptions, multihazard, stochastic programming.

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1. Introduction

A Supply Network (SN) is a configuration of endogenous resources and supply chain partners geographically deployed in order to serve a customer base. Strategic SN design decisions involve the determination of the number, location and mission of a set of facilities. At that level, the main objective of the firm is the design of a SN maximising shareholder value and maintaining this value at its best along a planning horizon. However, at design time the future environment under which the SN will evolve is unknown which complicates the strategic evaluation of potential designs. Traditional SN design approaches assume that the environment is deterministic, which give rise to classical location models (Klose and Drexl, 2005). Typical extensions of these models take into account random factors using stochastic programming (Birge and Louveaux, 1997) or depot failures using robust optimisation (Kouvelis and Yu, 1997). However, no comprehensive SN design methodology considering plausible future scenarios has been proposed. A recent review on supply chain networks design problems under uncertainty is found in Klibi *et al.*, (2009a).

A major preoccupation of contemporary businesses is the consideration of risk management issues when designing SNs. In addition to the random variables associated to business-as-usual factors, several catastrophic events have recently disrupted supply chain networks. Rice and Caniato (2003) and Christopher and Peck (2004) investigate network vulnerability to extreme unforeseen events such as natural disasters and strikes, and Sheffi (2005) examines the case of several companies who suffered from fires, earthquakes, floods, intentional attacks, etc. SNs are geographically dispersed across large regions which increase their exposure to extreme events and, in order to design robust SNs, the impact of such events must be considered. To this end, this paper considers the random, hazardous and deeply uncertain events that shape future SN environments. The challenge here is to elaborate a SN design methodology taking all these event types into account while remaining sufficiently synthetic to be practical. The approach proposed is based on the modeling of multihazard exposures and it involves the definition of network vulnerability sources and exposure levels, the estimation of multihazard arrival processes, and the assessment of multihazard consequences. The risk modeling concepts applied are based on Haimes (2004), Grossi and Kunreuther (2005), Kleindorfer and Saad (2005) and Banks (2006).

In this context, responsiveness and resilience become key elements to enhance the robustness of SN designs. Responsiveness policies are operational rules to deal with random supply and demand factors as well as disruptions. Sheffi (2005) defines resilience as the ability to bounce back from disruptions. Resilience strategies are predispositions of network resources fa-

vouring risk avoidance and mitigation. Currently most SNs have difficulty coping with emergencies (Lee, 2004), and they do not develop plans to protect against high-impact low likelihood events (Chopra and Sodhi, 2004). Recently, SN risk management strategies incorporating redundancy and flexibility have been proposed in the literature (Chopra and Sodhi, 2004; Lee, 2004; Sheffi, 2005; Tang, 2006; Snyder *et al.*, 2006). However, these strategies were never explicitly incorporated in SN design models. Using the location-transportation problem under uncertainty as a typical SN design problem, this paper introduces responsiveness and resiliency constructs into SN design models, and it investigates the performance of the resulting SN designs.

The rest of the paper is organized as follows. Section 2 describes the location-transportation problem under uncertainty and characterizes underlying demand and hazard processes. Section 3 presents a scenario-based SN design approach and proposes two anticipation-based design models using stochastic programming. Section 4 discusses risk avoidance and SN resilience, and it proposes three design models to improve SN resilience. Section 5 proposes a generic approach to generate plausible future scenarios, and to elaborate and evaluate SN designs. Computational results are presented and analysed in section 6. Finally, section 7 concludes the paper.

2. The Location-Transportation Problem under Uncertainty

The Location-Transportation Problem Context

The company considered purchases a product family from a number of supply sources. This product is sold to customers located in a large geographical area and hence it must be shipped to a large number of ship-to-points. In order to serve its customers, the company must implement a number of capacitated depots with similar processes and technology. For a given day, the capacity of a depot reflects the maximum throughput sustained by its resources. In addition to its regular capacity level, we assume that under normal business conditions, the depot can provide an additional capacity per day using local recourses (ex. overtime).

Customers order a varying quantity of product and the company wants to provide next day delivery from a single source using common or contract carriers. To this end, several transportation options are available, namely: single customer full truckloads (FTL), single customer partial truckloads (STL), multi-drop truckloads (MTL) or less than truckload (LTL) transportation. For a given day, when all the orders are in, the company plans its transportation for the next day and it requests from its carriers the trucks required to deliver products to ship-to-points. However, the network's depots are under the threat of disruptions and, consequently, their capacity to respond adequately to ship-to-point's orders can be perturbed. Therefore, in order to complete the orders received for a given day, the company relies first on its regular capacity, and second on a local recourse such as overtime. If this is not sufficient, external resources can be used to satisfy all its

customers. **Figure 1** illustrates the Location Transportation Problem (LTP) under uncertainty. This problem is an extension of the LTP under stochastic demand studied by Klibi *et al.* (2009).

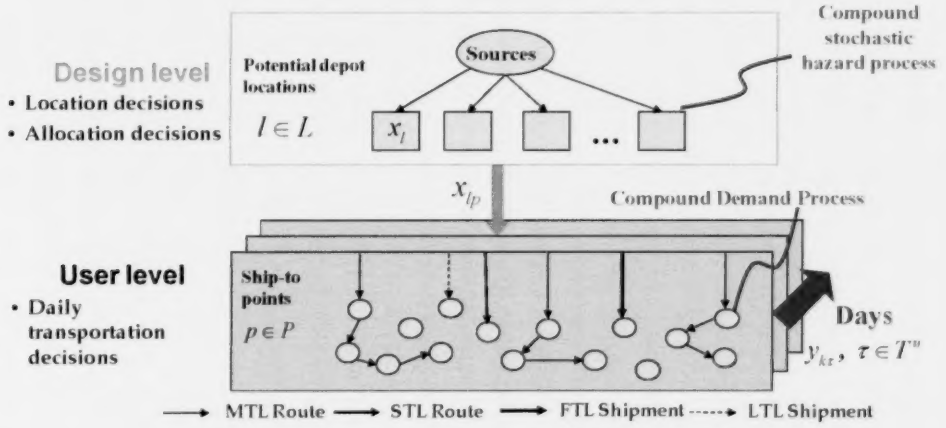

Figure 1- The LTP Structure under Uncertainty

Let L be the set of potential depots considered to perform distribution operations, P the set of all ship-to-points and P_l the subset of ship-to-points that could be served by depot $l \in L$. Also, let a_l be the capacity of depot l, i.e. the quantity of products it could ship during a day. At design time, strategic decisions are made on the subset of depots $\underline{L} \subset L$ to use during the planning horizon, and on their mission $\underline{P}_l \subset P_l, l \in \underline{L}$. These decisions are denoted by the vector $\mathbf{x}$. However, at design time, these decisions are taken under uncertainty and they must consider plausible future scenarios over a discrete planning horizon $\tau \in T^u$.

Demand and Hazard Modeling

Based on the information available at design time, two types of events shaping the business environment can be distinguished, namely random and hazardous events. Random events are related to business-as-usual operations, and hazardous events to low-probability high-impact disruptions. In this paper, random customer's demand and network's multihazards are modeled as compound stochastic processes. We assume that the demand of the SN ship-to-points $p \in P$ follows a compound process with a random order inter-arrival time q_p and a random order size o_p. The cumulative distribution functions of inter-arrival times and order sizes are denoted respectively by $F_p^q(.)$ and $F_p^o(.)$. The approach used to model hazards is based on Klibi and Martel (2009). Hazards are first amalgamated into meta-events with generic impacts called *multihazards*, and SN vulnerability sources are identified. Second, a compound stochastic process is defined to describe how multihazards occur in space and in time, and to specify incident's intensity and duration. Third the impact of hits on the SN is modelled using recovery functions.

In our context, the depots L and ship-to-points P constitute a set of network locations $N = P \cup L$. We assume that depots and ship-to points have different incident profiles in terms of impact and time to recovery and thus constitute two distinct *vulnerability sources*, denoted by s_L and s_P. The notation $s(n)$ is used to identify the vulnerability source of location $n \in N$. To map potential threats, the geographical territory in which the SN operates is partitioned into a set of *hazard zones* Z delineating areas with similar exposure characteristics. Using an exposure measure, each hazard zone $z \in Z$ is assigned to a discrete exposure level $g(z), g \in G$. Based on its geographical position each network location $n \in N$ is positioned in a hazard zone $z(n) \in Z$ and it has an exposure level $g(n) = g(z(n))$. We assume that multihazards occur independently in zones $z \in Z$, and that the time between their successive occurrences is a random variable λ_z characterized by a stochastic arrival process with cumulative distribution function $F_z^{\lambda}(.)$.

When zone $z \in Z$ is hit by a multihazard, the severity of the incident is characterized by two correlated random variables, expressed in terms of metrics depending on the vulnerability source $s \in \{s_L, s_P\}$, namely the *impact intensity* β_{zs}, with cumulative distribution function $F_{g(z)s}^{\beta}(.)$, and the *time to recovery* θ_{zs}. The time to recovery is related to the impact intensity through an *impact-duration function* $\theta_{zs} = f_s(\beta_{zs}) + \varepsilon_s$, where ε_s is a random error term with probability distribution function $F_s^{\varepsilon}(.)$. **Figure 2** illustrates this function for depots, in %-capacity loss, and for ship-to-points, in %-demand variation. Note that, following a hit on ship-to-points, first necessity products would see their demand raising but luxury products would see their demand dropping. As a single product family is considered here, the impact intensity provides a net effect for the entire product family. We can have a demand surge for some ship-to-points and a drop for others, however.

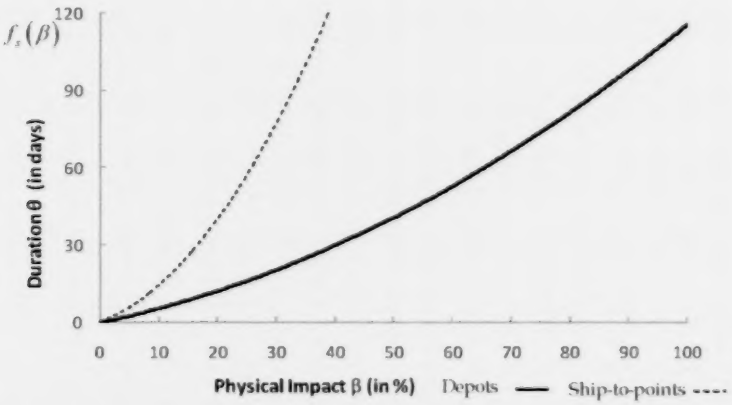

Figure 2- Impact-Duration Functions for Depots and Ship-to-Points

The occurrence of an incident in a hazard zone $z \in Z$ does not necessarily result in a hit of all the SN locations in that zone. Conditional attenuation probabilities α_n, $n \in N_z$, are defined to

reflect location hit likelihood. When a location $n \in N_z$ associated to vulnerability source s is hit, the *impact intensity* and the *time to recovery* are provided respectively by $\beta_n = \beta_{z(n)s(n)}$ and $\theta_n = \theta_{z(n)s(n)}$. Consider a multihazard hitting location $n \in N_z$ at the beginning of period $\tau' \in T^u$, and, to simplify the presentation, let the indexes $x = q, o, a$ be associated respectively to the customer order size (q) and order arrival (o) processes, and to the depot capacity process (a). The impact of a hit is not necessarily felt uniformly during the time to recovery: several phases can be observed, depending on the nature of the multihazard and of the vulnerability source (Sheffi, 2005). Such phase-dependent impacts can be characterized by defining discrete *recovery functions* $\rho^x_{n\tau} = r^x(\beta_n, \theta_n, \rho^x_{n\tau})$, $\tau = \tau', ..., \tau' + \theta_n - 1$, where $\rho^x_{n\tau}$ is a capacity/demand amplification percentage for process x at location n in period τ. The $\rho^x_{n\tau}$ value used as an argument in the function reflects amplification percentages before the hit and the function returns percentages after the hit. As illustrated in **Figure 3**, if the periods affected by the multihazard are not still recuperating from a previous incident, then the a priori percentages are $\rho^x_{n\tau}$=100%, $\forall x, n$, $\tau = \tau', ..., \tau' + \theta_n - 1$. The amplitude of the amplification depends on the multihazard impact intensity β_n. Using these recovery functions, the capacity and the demand can be calculated for specific periods and locations. For the order inter-arrival times and sizes, this gives rise to the perturbed random variables $q_{p\tau} = \rho^q_{p\tau} q_p$ and $o_{p\tau} = \rho^o_{p\tau} o_p$, $\tau = \tau', ..., \tau' + \theta_p - 1$, and to their associated distributions functions $F^q_{p\tau}(.)$ and $F^o_{p\tau}(.)$. For the depots, this yield perturbed capacity levels $a_{l\tau} = a_l \rho^a_{l\tau}$, $\tau = \tau', ..., \tau' + \theta_l - 1$.

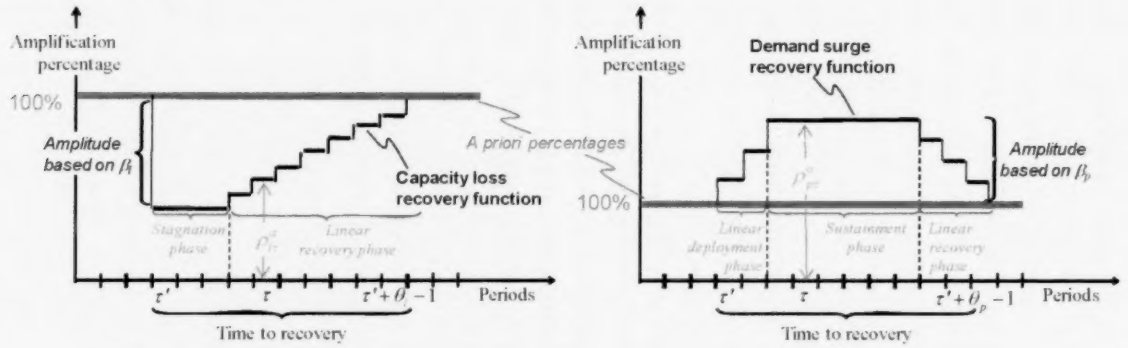

Figure 3- Recovery Function Examples for Depot l and Ship-to-Point p

Plausible Future Scenarios

The instantiation of the demand and multihazard processes described previously over all the possible values of the random variables involved yields a set Ω of plausible future scenarios with associated probabilities $\pi(\omega)$, $\omega \in \Omega$. The Monte Carlo procedure in **Figure 4** can be used to generate a scenario instance $\omega \in \Omega$. The procedure uses independent pseudorandom numbers u, uniformly distributed on the interval $[0,1]$, first to generate multihazard arrivals, second to generate recovery functions, and third to generate daily ship-to-point demands

$\mathbf{d}(\omega) = [d_{p\tau}(\omega)]_{p\in P,\ \tau\in T^u}$ and depot capacities $\mathbf{a}(\omega) = [a_{l\tau}(\omega)]_{l\in L,\ \tau\in T^u}$. The input parameters **a** and $\boldsymbol{\alpha}$ are capacity and attenuation probability vectors, respectively, and **F** denotes the set of all the previously defined probability distributions.

MonteCarlo$((N_z, z\in Z), T^u, \mathbf{a}, \boldsymbol{\alpha}, \mathbf{F}, (r^x, x = q,o,a); \mathbf{d}(\omega), \mathbf{a}(\omega))$

1) For all $z \in Z$, do:

Using the cumulative distribution of λ_z, generate multihazard arrival moments $\mathrm{T}_z \subseteq T^u$

Set $\rho^x_{n\tau} = 1$ for all $n \in N_z$, $\tau \in T^u$, $x = q,o,a$

For all $\tau' \in \mathrm{T}_z$, do:

Compute $\beta_{zs} = F^{-1}_{g(\varepsilon),s}(u)$ and $\theta_{zs} = \left\lceil f_s(\beta_{zs}) + F^{\varepsilon^{-1}}_s(u) \right\rceil$, $s \in \{s_L, s_P\}$

For all $n \in N_z \,|\, u \le \alpha_n$, do:

$$\rho^x_{n\tau} = r^x(\beta_{z(n)s(n)}, \theta_{z(n)s(n)}, \rho^x_{n\tau}),\ \tau = \tau', \ldots, \tau' + \theta_{z(n)s(n)} - 1,\ x = q,o,a$$

End For

End For

2) For all $p \in P$, do:

$\eta = 0$; $d_{p\tau}(\omega) = 0$, $\tau \in T^u$; $\tau = 1$; $F^q_{p\tau} = F^q_p$

While $\eta \le |T^u|$, do:

Compute the next order arrival time $\eta = \eta + F^{q^{-1}}_{p\tau}(u)$ and $\tau = \lceil \eta \rceil$

For $x = q,o$: Derive $F^x_{p\tau}$ from F^x_p and $\rho^x_{p\tau}$

Compute the daily demand $d_{p\tau}(\omega) = d_{p\tau}(\omega) + F^{o^{-1}}_{p\tau}(u)$

End While

End For

For all $l \in L$ and $\tau \in T^u$: Compute the daily capacity $a_{l\tau}(\omega) = a_l \rho^a_{l\tau}$

Figure 4- Scenario ω Generation Procedure

Some of the plausible future scenarios in Ω may involve only a few multihazard over the planning horizon but others may be much more chaotic. An intuitive measure to assess the risk associated to a scenario $\omega \in \Omega$ is the number of hits $\gamma(\omega)$ it undergoes during the planning horizon. **Figure 5** illustrates, for two SNs of different size, the distribution of the number of hits for a large sample of scenarios generated using procedure **MonteCarlo** with exponential multihazard inter-arrival times. In order to distinguish between the scenarios a decision maker would consider as acceptable, in term of the risks involved, and those that would raise a serious concern, we define a hazard tolerance level κ. This level is the maximum number of hits the decision maker can tolerate without serious concern. This tolerance level is used to partition Ω in two subsets: the set of low-hazard scenarios $\Omega^L = \{\omega \,|\, \gamma(\omega) \le \kappa\}$ with associated low-hazard probability $\pi^L = \Sigma_{\omega\in\Omega^L}\pi(\omega)$ and conditional scenario probabilities $\pi^L(\omega), \omega \in \Omega^L$, and the set of high-hazard scenarios $\Omega^H = \Omega \setminus \Omega^L$ with associated high-hazard probability $\pi^H = \Sigma_{\omega\in\Omega^H}\pi(\omega)$ and conditional scenario probabilities $\pi^H(\omega), \omega \in \Omega^H$. The risk associated to a SN depends on the

size of the territory it covers and on its density in terms of number of depots/points per unit area (Craighead *et al.*, 2007). For this reason, as illustrated in **Figure 5**, the distribution of hits is increasingly skewed towards the right as the size of the network increases. Consequently, the value κ selected also tends to increase with the size of the network considered. Also, the worst-case scenarios in the tail of the distribution will be of particular interest to us. They will be useful to assess the robustness of the SN designs considered.

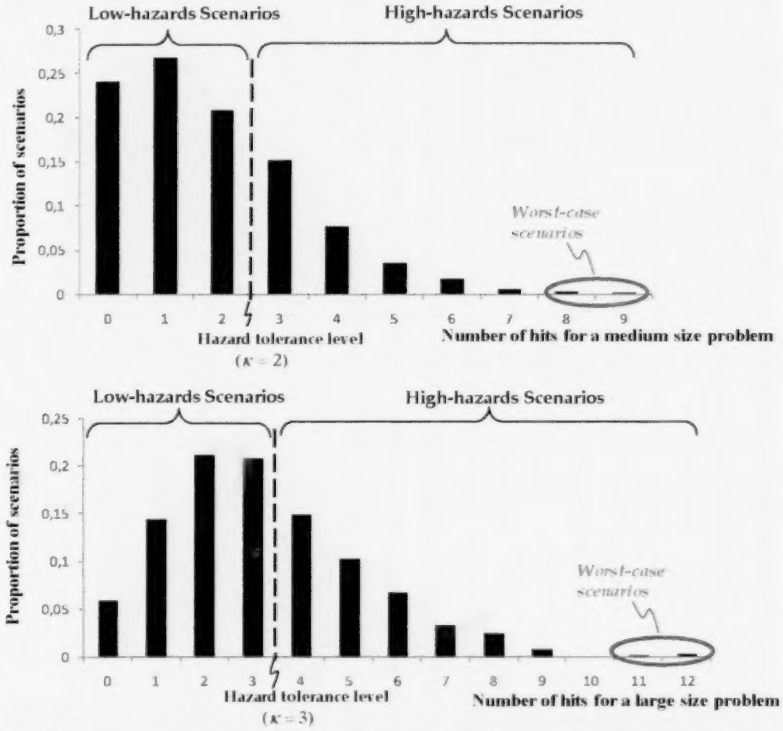

Figure 5- Distribution of the Number of Hits for a Large Scenario Sample

Finally, note that for a given scenario ω, on day τ, the depots capacity $a_{l\tau}(\omega)$, $l \in L$, is known and the set of depots L can be partitioned into operational depots $L_\tau(\omega) = \{l \mid a_{l\tau}(\omega) = a_l\}$ and partially operational depots $L_\tau^d(\omega) = \{l \mid a_{l\tau}(\omega) < a_l\}$. Similarly, the ship-to-points demand $d_{p\tau}(\omega)$, $p \in P$, is known and the set of ordering ship-to-points $P_\tau(\omega) = \{p \mid d_{p\tau}(\omega) > 0\}$ can be specified. The next section proposes a design approach for the LTP under uncertainty based on the risk modeling and scenario generation procedures presented here.

3. Scenario-Based SN Design Approach

The LTP under uncertainty is a hierarchical decision problem due to the temporal hierarchy between the location decisions and the transportation decisions. At design time depots location and mission decisions **x** must be made. However, these strategic decisions impose resource con-

straints on the network user's transportation decisions and they may restrict recourse actions in response to customer demands and hazards. On a daily basis, depot l users make shipping decisions, denoted by the vectors $\mathbf{y}_{l\tau}, \tau \in T^u$, in response to the orders received from customers. These decisions must be anticipated at design time since it is through them that net sales revenues are generated. In addition, due to hazards, operations can be perturbed by demand and/or depots disruptions. The recourse actions then employed to provide efficient service must also be anticipated to design a resilient network structure. This can be done by formulating the SN design problem as a two stage stochastic program with recourse. When based on exact anticipations, these SN design models are extremely complex and their solvability is an issue. To produce good designs, adequate precision-solvability tradeoffs must thus be made (Klibi *et al.*, 2009b). To this end, in what follows, we examine two approximate anticipations of user responses involving scenario-period sampling and transportation decisions aggregation.

User Response Model

For a given distribution network $\mathbf{x}$, a depots set $\underline{L} \subset L$ and depots business-as-usual missions $\underline{P}_l \subset P_l$, $l \in \underline{L}$, are set for all the days $\tau \in T^u$ of the planning horizon. In a single sourcing delivery context, each ship-to-point p is served by a unique depot denoted $l(p)$. Due to hazards, short-term variations in capacity and demand occur and recourse actions are necessary on a daily basis to provide an adequate response to customers. To respond adequately, the company must decide on a daily basis if the primary mission of depots is maintained or adapted. In the latter case, the company makes internal order reassignment decisions and, ultimately, recourse to external supply sources. Tomlin (2006) proposed operational tactics for managing disruptions based on rerouting ships. Once the order reassignment is done, the company makes shipping decisions, at each depot, with the objective to maximise sales revenues. To implement this, based on the response policy of the company, *order assignment* and *transportation* procedures must be elaborated.

For a given day τ under scenario ω, the set of ordering ship-to-points $P_\tau(\omega)$, their demand $d_{p\tau}(\omega), p \in P_\tau(\omega)$, and the depots daily capacity $a_{l\tau}(\omega), l \in \underline{L}$, are known. Thus, based on depots primary missions, revised daily assignment decisions $\underline{P}_{l\tau}(\omega)$, $l \in \underline{L}$, must be made to make sure that the depots capacity constraints $\sum_{p \in \underline{P}_\tau(\omega)} d_{p\tau}(\omega) \le a_{l\tau}(\omega), l \in \underline{L}$, are respected. Additionally, internal recourses (ex: overtime) or external resources can be used to satisfy unfulfilled orders. When a depot l is operational on day τ under scenario ω, additional capacity $\zeta_l a_l$, is available for use, where ζ_l is a fixed proportion of regular daily capacity. As illustrated in **Figure 6**, the stochastic demand level and depot capacity on each day dictate the kind of response decisions to take. When depot l is operational it serves its primary orders and it can process re-

assigned orders from other depots. When depot l is partially operational, however, it serves only a subset of its primary ship-to-point orders and the remaining ones are transferred.

Let P be a priority list ranking ship-to-points $p \in P$ in decreasing order of their importance. When all the SN orders have been received on a given day, we assume that list P is used to assign the most important customers to their primary depot $l(p)$ and to transfer the remaining orders to an alternative depot $l' \in \underline{L}_p \setminus \{l(p)\}$ or to an external supply source (identified using index $l = 0$). We assume that the reassignment policy used is based on a proximity rule (default policy), or on explicit or implicit instructions provided by the design model decisions. More specifically, we assume that the default reassignment policy is to supply ship-to-point p orders not shipped by $l(p)$ from the nearest depot in $\underline{L}_p \setminus \{l(p)\}$, that is to set $l'(p) = \arg\min_{l' \in \underline{L}_p \setminus \{l(p)\}} m_{l'p}$, where m_{lp} is the distance in miles between depot l and ship-to point p. If depot $l'(p)$ cannot ship the order, the company asks the external supply source $l = 0$ to make a direct shipment to ship-to-point p. On day τ, the ship-to-points supplied from the external depot are thus $P_{0\tau}(\omega) = P_\tau(\omega) \setminus \cup_{l \in \underline{L}} \underline{P}_{l\tau}(\omega)$.

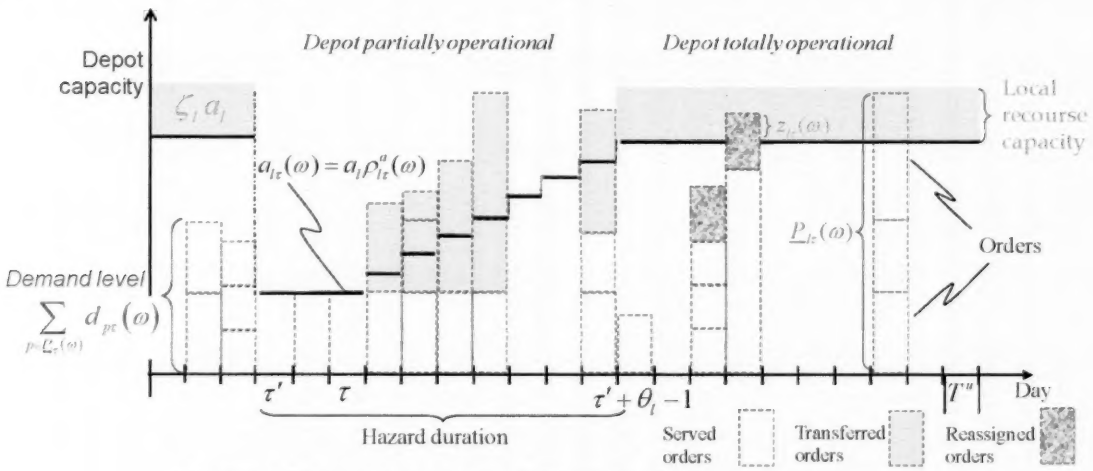

Figure 6- Demand Level at a Given Depot l under Scenario ω

Once reassignments have been made, the set $\underline{P}_{l\tau}(\omega)$ and the loads $d_{p\tau}(\omega)$, $p \in \underline{P}_{l\tau}(\omega)$, to deliver on day τ are known for each depot $l \in \underline{L} \cup \{0\}$. Then, the company can plan its transportation for the next day, and requests the trucks required for each depot from its carriers. These shipping decisions are made by the SN depot users in two steps. First, for loads that are larger than a truckload, a decision is made to ship as much as possible in FTL. We assume that a single type of vehicle is available to make full truckload shipments to point p. Let,

$y^{FTL}_{p\tau}(\omega)$: The number of truckloads shipped to point p on day τ
b^F: The capacity of vehicles used for FTL shipments
w_{lp}: The cost of a FTL shipment to point p from depot l

To determine the FTL shipments to make to point $p \in \underline{P}_{l\tau}(\omega)$, problem (1) below is solved by inspection. Then the residual loads to be inserted in the STL, MTL or LTL shipments are given by (2).

$$y_{p\tau}^{FTL}(\omega) = \arg\left(\max_{y=0,1,\ldots} b^F y \middle| b^F y \le d_{p\tau}(\omega) \right) \tag{1}$$

$$\bar{d}_{p\tau}(\omega) = d_{p\tau}(\omega) - b^F y_{p\tau}^{FTL}(\omega) \tag{2}$$

Next, the best delivery routes must be constructed. Let,

P_k: Ordered set of ship-to-points in route k

$K_{l\tau}(\omega)$: Set of non-dominated feasible STL, MTL or LTL routes (i.e. such that $P_k \subset \underline{P}_{l\tau}(\omega)$ and $\sum_{p \in P_k} \bar{d}_{p\tau}(\omega) \le b_k$, $k \in K_{l\tau}(\omega)$, where b_k is the capacity of route k vehicles) from depot l, on day τ, under scenario ω

w_k: Transportation cost of route $k \in K_{l\tau}(\omega)$

δ_{kp}: Binary coefficient taking the value 1 if ship-to-point p is covered by route k, and 0 otherwise

$y_{kl\tau}(\omega)$: Binary decision variable equal to 1 if route k is used from depot l on day τ under scenario ω, and 0 otherwise

For scenario ω, the best routes are obtained at depot l on day τ by solving the following transportation sub-problem:

$$C_{l\tau}^{u}(\omega) = \min_{\mathbf{y}_{l\tau}} \sum_{k \in K_{l\tau}(\omega)} w_k y_{kl\tau}(\omega) \tag{3}$$

subject to

$$\sum_{k \in K_{l\tau}(\omega)} \delta_{kp} y_{kl\tau}(\omega) = 1 \qquad p \in \underline{P}_{l\tau}(\omega) \tag{4}$$

$$y_{kl\tau}(\omega) \in \{0,1\} \qquad k \in K_{l\tau}(\omega) \tag{5}$$

where $C_{l\tau}^{u}(\omega)$ is the cost of the optimal shipments made by depot l on day τ under scenario ω. In this paper, the heuristic proposed by Klibi *et al.* (2009) to solve this problem is used. It is based on perturbed Clarke and Wright savings and 2-opt improvements. The cost of the transportation solution obtained with this heuristic is denoted by $\hat{C}_{l\tau}^{u}(\omega)$.

Furthermore, the shipments made on a daily basis generate sales revenues, and additional costs are incurred for recourse actions. Let,

v_l: Unit value of products shipped from depot l (taking into account the product production/procurement costs, inbound shipment costs, warehousing costs and inventory holding costs under normal operations)

u_p: Unit price of products sold to ship-to-point p

$z_{l\tau}(\omega)$: Recourse capacity needed at depot l on day τ ($z_{l\tau}(\omega) = \sum_{p \in \underline{P}_{l\tau}(\omega)} d_{p\tau}(\omega) - a_l$ if $l \in L_\tau(\omega)$ and 0 otherwise)

c_l^z: Additional unit cost incurred when recourse capacity is needed to ship products from depot l, with the consequence that the unit value of the products shipped becomes $v_l^z = v_l + c_l^z$

v^e: Unit cost of products supplied from the external emergency source using STL, MTL or LTL shipments

v^h: Unit cost of products supplied from the external source using FTL shipments

Since the emergency supply source would be used only in extreme cases, the costs v^e and v^h are assumed to be the same for all ship-to-points. These costs are external recourse penalties with values higher than product values and prices, i.e. such that $v_l < v_l^z < v^h < v^e$ for all l and $u_p < v^h < v^e$ for all p. From this, unit external supply loss can be defined as: $c_p^e = v^e - u_p$ and $c_p^h = v^h - u_p$, for all p. Under scenario ω, for day τ, the net revenues $\hat{R}_{l\tau}(\omega)$ generated by depot $l \in \underline{L}$ and the network loss for external recourses $\hat{C}_{0\tau}(\omega)$ can be calculated as follows:

$$\hat{R}_{l\tau}(\omega) = \sum_{p \in \underline{P}_{l\tau}(\omega)} \left(\left[(u_p - v_l) d_{p\tau}(\omega) \right] - c_l^z z_{l\tau}(\omega) - w_{lp} y_{p\tau}^{FTL}(\omega) \right) - \hat{C}_{l\tau}^u(\omega) \tag{6}$$

$$\hat{C}_{0\tau}(\omega) = \sum_{p \in \underline{P}_{0\tau}(\omega)} \left(c_p^e \overline{d}_{p\tau}(\omega) + c_p^h b^F y_{p\tau}^{FTL}(\omega) \right) \tag{7}$$

The **UserResponse** procedure described above is summarized in **Figure 7**, and it can be used to calculate the net revenues $\hat{R}^u(\mathbf{x}, \omega)$ generated over the planning horizon for a given SN design $\mathbf{x}$, under a scenarios ω.

Risk-Neutral Design Model

The strategic decisions to make here involve the selection of a subset of depots $\underline{L}^* \subset L$ to operate during the planning horizon T^u, and the assignment of ship-to-points $\underline{P}_l^* \subset P_l$, $l \in \underline{L}^*$ to these depots, to maximize total expected profits. An important aspect of the problem is that the mission of the selected depots, defined by their customer sets, $\underline{P}_l^*$, $l \in \underline{L}^*$ must remain the same for each day $\tau \in T^u$ of the planning horizon. To take adequate design decision we must anticipate how the company response policy, materialized in the response procedure implemented, will perform with these decisions. This implies that the transportation sub-problem (3)-(5) and the revenues and loss functions (6) and (7) must be incorporated in the design model. Let,

x_l: Binary variable equal to 1 if depot l is opened, and 0 otherwise

x_{lp}: Binary variable equal to 1 if ship-to point p is assigned to depot l, and 0 otherwise

$e_{lp\tau}(\omega)$: Binary variable equal to 1 if under scenario ω the ship-to point p order for day τ is shipped from the emergency source instead of its primary depot l, and 0 otherwise

$h_{lp\tau}(\omega)$: Integer variable giving the number of FTL shipments made to ship-to point p from the emergency source, instead of depot l, for day τ under scenario ω

Also, the additional unit costs incurred when products are shipped from the emergency supply source instead of from supply depot l are denoted by $c_l^e = v^e - v_l$ for STL, MTL or LTL shipments and by $c_l^h = v^h - v_l$ for FTL shipments.

UserResponse$(\mathbf{x},(l'(p),p\in P),\mathbf{a}(\omega),\mathbf{d}(\omega),(L_\tau(\omega),P_\tau(\omega),\tau\in T^u),\mathrm{P}\,;\hat{R}^u(\mathbf{x},\omega))$

For all $\tau\in T^u$, do:

Set $\underline{P}_{l\tau}(\omega)=\varnothing$, $l\in\underline{L}\cup\{0\}$; $a_{l\tau}(\omega)=(1+\zeta_l)a_l$, $l\in L_\tau(\omega)\cap\underline{L}$

Assign orders to depots

For all $p\in P_\tau(\omega)$ in order of the priority in P, do

If $a_{l(p)\tau}(\omega)\geq d_{p\tau}(\omega)$ then

Set $\underline{P}_{l(p)\tau}(\omega)=\underline{P}_{l(p)\tau}(\omega)\cup\{p\}$ and $a_{l(p)\tau}(\omega)=a_{l(p)\tau}(\omega)-d_{p\tau}(\omega)$

Else If $a_{l'(p)\tau}(\omega)\geq d_{p\tau}(\omega)$ then

Set $\underline{P}_{l'(p)\tau}(\omega)=\underline{P}_{l'(p)\tau}(\omega)\cup\{p\}$ and $a_{l'(p)\tau}(\omega)=a_{l'(p)\tau}(\omega)-d_{p\tau}(\omega)$

Else: $P_{0\tau}(\omega)=P_{0\tau}(\omega)\cup\{p\}$

End do

Compute depot revenues and network loss

For all $l\in\underline{L}$, do

Solve the transportation problem (3)-(5) with Klibi *et al.* heuristic (2009)

Compute depot l net revenues $\hat{R}_{l\tau}(\omega)$ with (6)

End do,

Compute the network loss for external recourses $\hat{C}_{0\tau}(\omega)$ with (7)

End do

Compute the SN net revenues $\hat{R}^u(\mathbf{x},\omega)=\sum_{\tau\in T^u}\left(\sum_{l\in\underline{L}}\hat{R}_{l\tau}(\omega)-\hat{C}_{0\tau}(\omega)\right)$

Figure 7- Response Procedure for Design x under Scenario ω

For a risk-neutral decision-maker, a SN design maximizing expected net revenues would be obtained by solving the following two-stage stochastic program with recourse:

$$R=\max_{\mathbf{x}}\sum_{S=L,H}\pi^S\sum_{\omega\in\Omega^S}\pi^S(\omega)R^{du}(\mathbf{x},\omega)-\sum_{l\in L}A_l x_l \qquad (8)$$

subject to

$$\sum_{l\in L_p}x_{lp}=1 \qquad p\in P \qquad (9)$$

$$x_{lp}\leq x_l \qquad l\in L,\ p\in P_l \qquad (10)$$

$$x_l, x_{lp}\in\{0,1\} \qquad l\in L,\ p\in P_l \qquad (11)$$

Based on (3)-(6), the optimal value $R^{du}(\mathbf{x},\omega)$ of the second stage program for design $\mathbf{x}$ and scenario ω is given by:

$$R^{du}(\mathbf{x},\omega)=\sum_{\tau\in T^{w}}\left[\sum_{l\in L}\sum_{p\in P_{\tau}^{s}(\omega)\cap P_{l}^{s}}\left(\left[\left(u_{p}-v_{l}\right)d_{p\tau}(\omega)\right]x_{lp}-w_{lp}\left[y_{p\tau}^{FTL}(\omega)x_{lp}-h_{lp\tau}(\omega)\right]\right)-C_{\tau}^{*du}(\mathbf{x},\omega)\right] \quad (12)$$

with

$$C_{\tau}^{*du}(\mathbf{x},\omega)=\min\sum_{l\in L}\left[\sum_{k\in K_{l\tau}(\omega)}w_{k}y_{kl\tau}(\omega)+c_{l}^{z}z_{l\tau}(\omega)+\sum_{p\in P_{\tau}^{s}(\omega)\cap P_{l}^{s}}\left[c_{l}^{e}\overline{d}_{p\tau}(\omega)e_{lp\tau}(\omega)+c_{l}^{h}b^{F}h_{lp\tau}(\omega)\right]\right] \quad (13)$$

subject to

$$\sum_{k\in K_{l\tau}(\omega)}\delta_{kp}y_{kl\tau}(\omega)+e_{lp\tau}(\omega)=x_{lp} \qquad l\in L,\ p\in P_{\tau}(\omega)\cap P_{l} \quad (14)$$

$$h_{lp\tau}(\omega)\le y_{p\tau}^{FTL}(\omega)x_{lp} \qquad l\in L,\ p\in P_{\tau}(\omega)\cap P_{l} \quad (15)$$

$$\sum_{k\in K_{l\tau}(\omega)}\left(\left[\sum_{p\in P_{\tau}^{s}(\omega)\cap P_{l}^{s}}\delta_{kp}\overline{d}_{p\tau}(\omega)\right]y_{kl\tau}(\omega)\right)+\sum_{p\in P_{\tau}^{s}(\omega)\cap P_{l}^{s}}b^{F}y_{p\tau}^{FTL}(\omega)x_{lp} \le a_{l\tau}(\omega)+z_{l\tau}(\omega)+\sum_{p\in P_{\tau}^{s}(\omega)\cap P_{l}^{s}}b^{F}h_{lp\tau}(\omega) \qquad l\in L \quad (16)$$

$$z_{l\tau}(\omega)\le\zeta_{l}a_{l},\ l\in L_{\tau}(\omega); \qquad z_{l\tau}(\omega)\le 0,\ l\in L_{\tau}^{d}(\omega) \quad (17)$$

$$y_{kl\tau}(\omega),e_{lp\tau}(\omega)\in\{0,1\},z_{l\tau}(\omega),h_{lp\tau}(\omega)\ integer \qquad k\in K_{l\tau}(\omega),\ l\in L,\ p\in P_{\tau}(\omega)\cap P_{l} \quad (18)$$

In the first term of objective function (8) the expected net revenues are calculated and in the second term the depot fixed costs are subtracted to get expected profits. Constraints (9) in the first stage program enforce single depot assignments for ship-to-points and constraints (10) limit ship-to-point assignments to opened depots. For design $\mathbf{x}$, under scenario ω, expression (12) estimates the anticipated net revenues based on allocation decisions, depots FTL shipment costs and other transportation and recourse costs obtained by solving the second stage program (13)-(18). The objective function (13) computes STL, MTL or LTL shipment costs, depot overcapacity costs and emergency supply costs. Constraints (14) are route coverage and also coupling relations ensuring that daily routes selection respects depots mission decisions for the second stage. Constraints (15) insure that FTL recourses are employed for day τ only if ship-to-point p is assigned to depot l. Constraints (16) ensure that each depot l capacity is respected given the demand on day τ for the assigned ship-to-points. Constraints (17) limit local recourse proportionally to the depot capacity.

Design Models Based on Approximate Anticipations

The stochastic program (8)-(18) is intractable due to the infinite number of plausible future scenarios and the extremely large number of possible transportation routes. Thus, approximate anticipations must be used to obtain solvable SN design models. To this end, based on the work

of Klibi *et al.* (2009b), two approximate anticipations providing good quality-solvability trade-offs are considered in this paper. The first one is obtained through scenario and period sampling, and the second one through transportation decision aggregations transforming the stochastic LTP into a stochastic location-allocation problem.

To reduce the stochastic complexity of the problem, it can be reformulated using a random sample of scenarios generated with the **MonteCarlo** procedure presented in **Figure 4**. This type of Sample Average Approximation (SAA) method (Shapiro, 2003) has been successfully applied to solve several SN design problems (Santoso *et al.*, 2005; Vila *et al.*, 2007; Klibi *et al.*, 2009). Given our partition of the plausible future scenarios in two subsets Ω^L and Ω^H, the idea in our context is first to generate a large independent sample of M equiprobable scenarios $\Omega^M \subset \Omega$ using procedure **MonteCarlo**, and to partition it into the subset Ω^{M_L} of M_L low-hazard scenarios and the subset Ω^{M_H} of M_H high-hazard scenarios. An estimate of the probabilities π^L and π^H is then given by $\bar{\pi}_L = M_L/M$ and $\bar{\pi}_H = 1 - \bar{\pi}_L$. Second, a small sample Ω^{m_L} of m_L scenarios is randomly selected in Ω^{M_L} and a small sample Ω^{m_H} of m_H scenarios is randomly selected in Ω^{M_H} to get $\Omega^m = \Omega^{m_L} \cup \Omega^{m_H}$. These sets of equiprobable scenarios can then be used to formulate a SAA model. Unfortunately, the multi-period SAA model obtained is still extremely difficult to solve with current solvers. Since the demand processes of the stochastic LTP are stationary, Klibi *et al.* (2009b) proposed to further simplify the problem by period sampling, i.e. by considering only a subset $\hat{T} \subset T^u$ of daily periods (for example, one randomly selected day per week) with associated ship-to-point demands $d_{pt}(\omega), p \in P_t(\omega), \omega \in \Omega^m, t \in \hat{T}$, and depot capacities $a_{lt}(\omega), l \in L, \omega \in \Omega^m, t \in \hat{T}$. The net revenues must then be multiplied by the period shrinking factor $|T^u|/|\hat{T}|$ to obtain an adequate approximation of the total expected profits.

By using the probabilities π^L and π^H in the objective function (8), the total expected profit is obtained, which is adequate for a risk-neutral decision-maker. However, if the decision-maker is risk-averse, these probabilities need to be replaced by weights $\hat{\pi}_H > \pi^H$ and $\hat{\pi}_L = 1 - \hat{\pi}_H$ to give more importance to high-hazard scenarios (Klibi and Martel, 2009). For the SAA model, the value of these weights are based on the estimated probability $\bar{\pi}_H$. Also, since generating all possible routes yield extremely large models, the SAA model proposed is based on adequately generated (Klibi *et al.*, 2009b) subsets of routes $\hat{K}_{l\tau}(\omega) \subset K_{l\tau}(\omega)$, $l \in L$, $\tau \in T^u$, $\omega \in \Omega^m$. Given these elements, program (8)-(18) is transformed into the following approximate anticipation location-transportation model (**M1**):

$$\hat{R}_{\mathrm{M1}} = \max \frac{|T^u|}{|\hat{T}|} \sum_{S \subseteq L, H} \frac{\hat{\pi}_S}{m_S} \left\{ \sum_{\omega \in \Omega^{m_S}} \sum_{t \in \hat{T}} \sum_{l \in L} \left[\sum_{p \in P_t(\omega) \cap P_l} \left(\left[\left(u_p - v_l \right) d_{pt}(\omega) \right] x_{lp} - w_{lp} \left[y_{pt}^{FTL}(\omega) x_{lp} - h_{lpt}(\omega) \right] \right) \right.\right.$$
$$\left.\left. - \sum_{k \in \hat{K}_{lt}(\omega)} w_k y_{klt}(\omega) - c_l^z z_{lt}(\omega) - \sum_{p \in P_t(\omega) \cap P_l} \left[c_l^e \bar{d}_{pt}(\omega) e_{lpt}(\omega) + c_l^h b^F h_{lpt}(\omega) \right] \right] \right\} - \sum_{l \in L} A_l x_l \tag{19}$$

subject to

$$\sum_{k\in\hat{K}_{lt}(\omega)} \delta_{kp}\, y_{klt}(\omega) + e_{lpt}(\omega) = x_{lp} \qquad l\in L,\ p\in P_t(\omega)\cap P_l,\ \omega\in\Omega^m,\ t\in\hat{T} \qquad (20)$$

$$h_{lpt}(\omega) \le y_{pt}^{FTL}(\omega)\, x_{lp} \qquad l\in L,\ p\in P_t(\omega)\cap P_l,\ \omega\in\Omega^m,\ t\in\hat{T} \qquad (21)$$

$$\sum_{k\in\hat{K}_{lt}(\omega)} \Big(\Big| \sum_{p\in P_t(\omega)\cap P_l} \delta_{kp}\bar{d}_{pt}(\omega) \Big| y_{klt}(\omega) \Big) + \sum_{p\in P_t(\omega)\cap P_l} b^F y_{pt}^{FTL}(\omega)\, x_{lp}$$
$$\le a_{lt}(\omega) + z_{lt}(\omega) + \sum_{p\in P_t(\omega)\cap P_l} b^F h_{lpt}(\omega) \qquad l\in L,\ \omega\in\Omega^m,\ t\in\hat{T} \qquad (22)$$

$$z_{lt}(\omega) \le \zeta_l a_l,\ l\in L_t(\omega); \qquad z_{lt}(\omega)\le 0,\ l\in L_t^d(\omega) \qquad \omega\in\Omega^m,\ t\in\hat{T} \qquad (23)$$

$$y_{klt}(\omega), e_{lpt}(\omega)\in\{0,1\}, z_{lt}(\omega), h_{lpt}(\omega)\ integer \qquad l\in L,\ p\in P_t(\omega)\cap P_l,\ k\in\hat{K}_{lt}(\omega),\ \omega\in\Omega^m,\ t\in\hat{T} \qquad (24)$$

and to the location-allocation constraints (9)-(11).

Model **M1** is much simpler than the original model but it is still difficult to solve when the set of plausible future scenarios Ω^m is large. Additional simplifications are possible when the transportation sub-problems are replaced by flow variables between depots and ship-to-points. When this is done, routing costs are replaced by unit flow costs $\hat{w}_{lp}$ between depots $l\in L$ and ship-to-points $p\in P_t$. These costs are estimated by regression using daily historical data (Klibi *et al.*, 2009b). This introduces second-stage binary variable $x_{lpt}(\omega)$ which takes value 1 if ship-to-point p is served by depot l in period t under scenario ω, and 0 otherwise. Also, under scenario ω, the model needs a binary recourse variable $e_{pt}(\omega)$ to specify if products are supplied to ship-to-point p by the emergency source in period t. An average unit net revenue $\left(u_p - \overline{v}^e\right)$, with $\overline{v}^e = \left(v^e + v^h\right)/2$, is associated to these flows. The SAA formulation of the stochastic location-allocation model thus obtained has the following form (**M2**):

$$\hat{R}_{M2} = \max \frac{|T^u|}{|\hat{T}|} \sum_{S=L,H} \frac{\hat{\pi}_S}{m_S} \left\{ \sum_{\omega\in\Omega^{m_S}} \sum_{t\in\hat{T}} \left[\sum_{l\in L} \left(\sum_{p\in P_t(\omega)\cap P_l} \left[\left(u_p - v_l - \hat{w}_{lp}\right) d_{pt}(\omega) \right] x_{lpt}(\omega) - c_l^z z_{lt}(\omega) \right) \right.\right.$$
$$\left.\left. + \left(u_p - \overline{v}^e\right) \sum_{p\in P_t(\omega)} d_{pt}(\omega) e_{pt}(\omega) \right] \right\} - \sum_{l\in L} A_l x_l \qquad (25)$$

subject to

$$\sum_{l\in L_p} x_{lpt}(\omega) + e_{pt}(\omega) = 1 \qquad p\in P_t(\omega), \omega\in\Omega^m, t\in\hat{T} \qquad (26)$$

$$x_{lpt}(\omega) \le x_{lp} \qquad l\in L, p\in P_t(\omega)\cap P_l, \omega\in\Omega^m, t\in\hat{T} \qquad (27)$$

$$\sum_{p\in P_t(\omega)\cap P_l} d_{pt}(\omega) x_{lpt}(\omega) \le a_{lt}(\omega) + z_{lt}(\omega) \qquad l\in L, \omega\in\Omega^m, t\in\hat{T} \qquad (28)$$

$$z_{lt}(\omega) \le \zeta_l a_l,\ l\in L_t(\omega); \qquad z_{lt}(\omega)\le 0,\ l\in L_t^d(\omega) \qquad \omega\in\Omega^m, t\in\hat{T} \qquad (29)$$

$$e_{pt}(\omega)\ge 0, z_{lt}(\omega)\ge 0 \qquad l\in L, p\in P_t(\omega)\cap P_l, \omega\in\Omega^m, t\in\hat{T} \qquad (30)$$

$$x_{lpt}(\omega)\in\{0,1\} \qquad l\in L, p\in P_t(\omega)\cap P_l, \omega\in\Omega^m, t\in\hat{T} \qquad (31)$$

and to the location-allocation constraints (9)-(11).

Since **M2** is solved relatively easily, larger scenario samples can be used. Note that a gross anticipation could also be obtained by neglecting uncertainty, and by using the familiar capacitated location-allocation model found in the literature. This requires the calculation of annual average demands $\hat{D}_p$ from the demand process parameters, and the estimation of average unit transportation costs $\hat{w}_{lp}$ by regression (Klibi *et al.*, 2009b). The depots capacity can be set to $\left|T^u\right|a_l$, $l \in L$, which is clearly an overestimation. The following formulation results (**M3**):

$$\hat{R}_{M3} = \max_{\mathbf{x}} \sum_{l \in L} \sum_{p \in P_l} \left\{ \left(u_p - v_l - \hat{w}_{lp} \right) \hat{D}_p \right\} x_{lp} - \sum_{l \in L} A_l x_l \tag{32}$$

$$\text{subject to } \sum_{p \in P_l} \hat{D}_p x_{lp} \leq \left|T^u\right| a_l \qquad l \in L \tag{33}$$

and to location-allocation constraints (9)-(11).

4. Resilience Strategy Formulations

As mentioned, due to demand randomness and hazards, SN user operations can be perturbed and response actions must be tailored to occurring events to maintain business continuity. However, response policies are rarely anticipated in SN design models. The stochastic programming models proposed in the previous section anticipate response policies through the use of the second stage variables $y_{klt}(\omega)$, $z_{lt}(\omega)$, $e_{lpt}(\omega)$ and $h_{lpt}(\omega)$. Due to the costs associated to these variables, the models position the depots and specify their mission to avoid risks as much as possible. Moreover, by considering the risk attitude of the decision-maker, the models can be more or less drastic in their effort to avoid hazards. For these reasons, models **M1** and **M2** are appropriate mainly when pursuing a *Risk Avoidance* (**RA**) strategy. A discussion of risk avoidance in supply chain management is found in Manuj and Mentzer (2008).

Despite efforts to avoid risks as much as possible, it is clear that the SN designed will be hit by occasional disruptions. Given this, the question then becomes: what kind of risk mitigation constructs could be incorporated in the design models to obtain more robust SN designs? In other words, how can we design the network to make sure that it will bounce back quickly when hit? This can be done by investing in flexible and redundant network structures before they are needed (Sheffi, 2005), and by providing better resilience policy instructions. This is the domain of *resilience strategies*. A main concern is to design robust SN not only to hedge against major disruptions but also to improve business-as-usual operations. Despite the growing number of papers on the importance of the resilience concept, little has been done to incorporate it in SN design models. However, several modeling constructs found in the literature on coverage (Church and Revelle, 1974), vector assignment (Weaver and Church, 1985) and reliability (Snyder *et al.*,

2006; Tomlin, 2006; Murray and Grubesic, 2007) models can help to foster resilience.

Our aim in this section is to propose three LTP network design models to improve resilience when a single sourcing policy is applied. These models distinguish themselves from **M1** and **M2** by the fact that they strive to provide either explicit or implicit instructions on the back-up depot $l'(p)$ to use when applying the response procedure described in **Figure 7**. The first model finds the optimal primary and back-up depots to use for each ship-to-point. The second model allows multiple sourcing for each ship-to-point in order to reduce the risk of disruption when the primary depot is hit. The idea behind the third model is to offer a better network coverage by ensuring that at least two depots are geographically located within desired distances of each ship-to-point. **Figure 8** illustrates the three resilience strategy formulations proposed. The next subsections extent models **M1** and **M2** for each of these formulations.

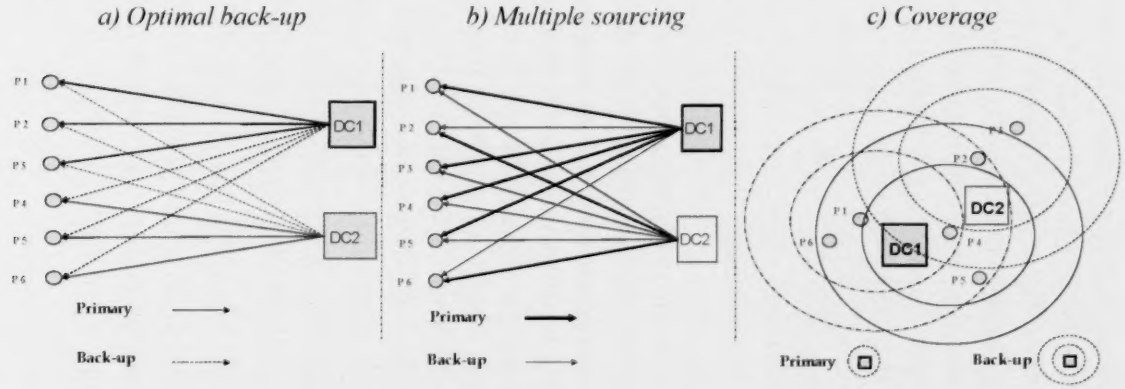

Figure 8- Resilience Strategy Formulations

Optimal Back-up Formulations (R1)

The aim of these formulations is to specify the backup depot to use when the primary depot assigned to a ship-to-point cannot supply its orders (**Figure 8**a). The formulations proposed are inspired by the work of Weaver and Church (1985) and Snyder *et al.*, (2006) on the vector assignment problem and on the reliable fixed charge location problem, respectively. Binary variables are defined to specify primary allocation decisions x^1_{lp} and backup allocation decisions x^2_{lp}. The variables x^r_{lp}, $r=1,2$, take the value 1 if ship-to-point p is allocated to depot l as level r (primary or back-up) supply facility, and 0 otherwise. In the models, these mission specification variables are first stage variables and thus they remain the same for all the periods of the planning horizon. However, for each period t of scenario $\omega \in \Omega^m$, a second stage binary variable $x_{lpt}(\omega)$ needs to be introduced: it takes the value 1 if ship-to-point p is supplied by depot l in period t under scenario ω, and 0 otherwise. As before, an external emergency source takes over

when both the primary and backup depots are unable to supply a given ship-to-point. This leads to the transformation of model **M1** into the following SAA model (**M1-R1**):

$$\hat{R}_{\text{M1-R1}} = \max \frac{|T^u|}{|\hat{T}|} \sum_{S=1,H} \frac{\hat{\pi}_S}{m_S} \left\{ \sum_{\omega^s \in \Omega^{m_S}} \sum_{t \in \hat{T}} \sum_{l \in L} \left[\sum_{p \in P_t(\omega) \cap P_l} \left(\left[\left(u_p - v_l \right) d_{pt}(\omega) \right] x_{lpt}(\omega) - w_{lp} \left[y_{pt}^{FTL}(\omega) x_{lpt}(\omega) - h_{lpt}(\omega) \right] \right) \right. \right.$$
$$\left. \left. - \sum_{k \in \hat{K}_{lt}(\omega)} w_k y_{klt}(\omega) - c_l^z z_{lt}(\omega) - \sum_{p \in P_t(\omega) \cap P_l} \left[c_l^e \bar{d}_{pt}(\omega) e_{lpt}(\omega) - c_l^h b^F h_{lpt}(\omega) \right] \right] \right\} - \sum_{l \in L} A_l x_l \tag{34}$$

subject to

$$\sum_{l \in L_p} x_{lp}^r = 1 \qquad p \in P, r = 1,2 \tag{35}$$

$$\sum_{r=1,2} x_{lp}^r \le x_l \qquad p \in P_l, l \in L \tag{36}$$

$$x_{lpt}(\omega) \le \sum_{r=1,2} x_{lp}^r \qquad l \in L, p \in P_t(\omega) \cap P_l, \omega \in \Omega^m, t \in \hat{T} \tag{37}$$

$$h_{lpt}(\omega) \le y_{pt}^{FTL}(\omega) x_{lpt}(\omega) \qquad l \in L, p \in P_t(\omega) \cap P_l, \omega \in \Omega^m, t \in \hat{T} \tag{38}$$

$$\sum_{k \in \hat{K}_{lt}(\omega)} \left(\left| \sum_{p \in P_t(\omega) \cap P_l} \delta_{kp} \bar{d}_{pt}(\omega) \right| y_{klt}(\omega) \right) + \sum_{p \in P_t(\omega) \cap P_l} b^F y_{pt}^{FTL}(\omega) x_{lpt}(\omega)$$
$$\le a_{lt}(\omega) + z_{lt}(\omega) + \sum_{p \in P_t(\omega) \cap P_l} b^F h_{lpt}(\omega) \qquad l \in L, \omega \in \Omega^m, t \in \hat{T} \tag{39}$$

$$\sum_{k \in \hat{K}_{lt}(\omega)} \delta_{kp} y_{klt}(\omega) + e_{lpt}(\omega) = x_{lpt}(\omega) \qquad l \in L, p \in P_t(\omega) \cap P_l, \omega \in \Omega^m, t \in \hat{T} \tag{40}$$

$$\sum_{l \in L_p} x_{lpt}(\omega) = 1 \qquad p \in P_t(\omega), \omega \in \Omega^m, t \in \hat{T} \tag{41}$$

$$x_l, x_{lp}^r, x_{lpt}(\omega) \in \{0,1\} \qquad l \in L, p \in P_t(\omega) \cap P_l, \omega \in \Omega^m, t \in \hat{T} \quad r = 1,2 \tag{42}$$

and to constraints (23)-(24).

Constraints (35) and (36) ensure that each ship-to point has distinct primary and backup depots. Constraints (37) guarantee that shipments are made only from primary or backup depots. Constraints (41) guarantee that the single sourcing rule is respected for every period.

By proceeding similarly, **M2** can be transformed into the following backup optimization model (**M2-R1**):

$$\hat{R}_{\text{M2-R1}} = \max \frac{|T^u|}{|\hat{T}|} \sum_{S=1,H} \frac{\hat{\pi}_S}{m_S} \left\{ \sum_{\omega^s \in \Omega^{m_S}} \sum_{t \in \hat{T}} \left[\sum_{l \in L} \left(\sum_{p \in P_{lt}(\omega)} \left[\left(u_p - v_l - \hat{w}_{lp} \right) d_{pt}(\omega) \right] x_{lpt}(\omega) - c_l^z z_{lt}(\omega) \right) \right. \right.$$
$$\left. \left. + \left(u_p - \bar{v}^e \right) \sum_{p \in P_t(\omega)} d_{pt}(\omega) e_{pt}(\omega) \right] \right\} - \sum_{l \in L} A_l x_l \tag{43}$$

subject to constraints (23), (26)-(28), (30), (35)-(37) and (42).

Note that these models include a large number of binary variables, which complicates their resolution. The instruction provided by the models to the response procedure is the following: $l(p) = l \mid x^1_{lp} = 1$ and $l'(p) = l \mid x^2_{lp} = 1$, $p \in P$.

Multiple Sourcing Formulations (R2)

The idea behind these formulations is to allow multiple sourcing for each ship-to-point (**Figure 8**b) to identify natural supply depots backups, as opposed to forced backups as in the previous section. For formulation **M1**, this is done essentially by removing constraints (9) from the first-stage program, and by introducing second-stage assignment variables $x_{lpt}(\omega)$ with value 1 when depot l supplies ship-to-point p in period t under scenario ω. The following model results (**M1-R2**):

$$\hat{R}_{\text{M1-R2}} = \max \frac{|T^u|}{|\hat{T}|} \sum_{S \subseteq L,H} \frac{\hat{\pi}_S}{m_S} \left\{ \sum_{\omega \in \Omega^{m_S}} \sum_{t \in T} \sum_{l \in L} \left[\sum_{p \in P_l(\omega) \cap P_l} \left(\left[\left(u_p - v_l \right) d_{pt}(\omega) \right] x_{lpt}(\omega) - w_{lp} \left[y^{FTL}_{pt}(\omega) x_{lpt}(\omega) - h_{lpt}(\omega) \right] \right) \right. \right.$$
$$\left. \left. - \sum_{k \in \bar{K}_{lt}(\omega)} w_k v_{klt}(\omega) - c^z_l z_{lt}(\omega) - \sum_{p \in P_l(\omega) \cap P_l} \left[c^e_l \bar{d}_{pt}(\omega) e_{lpt}(\omega) + c^h_l h^F h_{lpt}(\omega) \right] \right] \right\} - \sum_{l \in L} A_l x_l \tag{44}$$

subject to constraints (10)-(11), (23)-(24), (27), (31) and (38)-(41).

When this model is solved, several depots may be used to serve a given ship-to-point during the planning horizon. The primary depot for a ship-to-point is then defined as the one shipping the largest quantity of products to this point during the planning horizon. The depot with the second largest shipment quantity is specified as the backup depot. More specifically, we define:

$$l(p) = \arg\max_{l \in \underline{L}_p} \frac{1}{m} \sum_{\omega} \sum_{t} d_{pt}(\omega) x_{lpt}(\omega) \text{ and } l'(p) = \arg \max_{l \in \underline{L}_p \setminus \{l(p)\}} \frac{1}{m} \sum_{\omega} \sum_{t} d_{pt}(\omega) x_{lpt}(\omega)$$

Note that the backup depot is specified only for ship-to-points supplied by more than one depot during the planning horizon.

For formulation **M2**, the second-stage program is defined in terms of continuous flow variables instead of binary assignment variables, namely: $x_{lpt}(\omega)$ the quantity of product supplied by depot l to ship-to point p in period t under scenario ω, and $e_{pt}(\omega)$ the quantity supplied to p by the emergency supply source. This leads to the following model (**M2-R2**):

$$\hat{R}_{\text{M2-R2}} = \max \frac{|T^u|}{|\hat{T}|} \sum_{S \subseteq L,H} \frac{\hat{\pi}_S}{m_S} \left\{ \sum_{\omega \in \Omega^{m_S}} \sum_{t \in T} \left[\sum_{l \in L} \left(\sum_{p \in P_l(\omega) \cap P_l} \left[u_p - v_l - \hat{w}_{lp} \right] x_{lpt}(\omega) - c^z_l z_{lt}(\omega) \right) \right. \right.$$
$$\left. \left. + \left(u_p - \bar{v}^e \right) \sum_{p \in P_l(\omega)} e_{pt}(\omega) \right] \right\} - \sum_{l \in L} A_l x_l \tag{45}$$

subject to

$$\sum_{l\in L} x_{lpt}(\omega) + e_{pt}(\omega) = d_{pt}(\omega) \qquad p \in P_t(\omega), t \in \hat{T}, \omega \in \Omega^m \tag{46}$$

$$x_{lpt}(\omega) \le d_{pt}(\omega) x_{lp} \qquad l \in L, p \in P_t(\omega) \cap P_l, t \in \hat{T}, \omega \in \Omega^m \tag{47}$$

$$\sum_{p \in P_{lt}(\omega)} x_{lpt}(\omega) \le a_{lt}(\omega) + z_{lt}(\omega) \qquad l \in L, t \in \hat{T}, \omega \in \Omega^m \tag{48}$$

$$x_{lpt}(\omega) \ge 0 \qquad l \in L, p \in P_t(\omega) \cap P_l, t \in \hat{T}, \omega \in \Omega^m \tag{49}$$

and to constraints (10)-(11) and (29)-(30).

The instruction provided by the model in this case is:

$$l(p) = \arg\max_{l \in L_p} \frac{1}{m} \sum_{\omega} \sum_{t} x_{lpt}(\omega) \text{ and } l'(p) = \arg\max_{l \in L_p \setminus \{l(p)\}} \frac{1}{m} \sum_{\omega} \sum_{t} x_{lpt}(\omega)$$

Coverage Formulations (R3)

As in classical covering problems (Church and Revelle, 1974), the idea behind the third formulation is to offer better network coverage by using proximity criteria specifying maximum primary/backup depot to ship-to-point distances (**Figure 8c**). Let $L_p^2 \subseteq L_p$ be the set of depots located within the backup distance specified for ship-to-point p, and $L_p^1 \subset L_p^2$ be the set of depots located within the primary distance specified. This formulation imposes that for each ship-to-point $p \in P$, at least one depot is in L_p^1 and at least 2 depots are in L_p^2. This tends to increase the number of opened depots and to spread them more evenly on the territory. This leads to the transformation of model **M1** into the following SAA model (**M1-R3**):

$$\hat{R}_{\text{M1-R3}} = \max \frac{|T^u|}{|\hat{T}|} \sum_{S=1,H} \frac{\hat{\pi}_S}{m_S} \left\{ \sum_{\omega \in \Omega^{m_S}} \sum_{t \in \hat{T}} \sum_{l \in L} \left[\sum_{p \in P_t(\omega) \cap P_l} \left(\left[\left(u_p - v_l \right) d_{pt}(\omega) \right] x_{lp} - w_{lp} \left[y_{pt}^{FTL}(\omega) x_{lp} - h_{lpt}(\omega) \right] \right) \right. \right.$$
$$\left. \left. - \sum_{k \in K_{lt}(\omega)} w_k v_{klt}(\omega) - c_l^z z_{lt}(\omega) - \sum_{p \in P_t(\omega) \cap P_l} \left[c_l^e \bar{d}_{pt}(\omega) e_{lpt}(\omega) + c_l^h b^F h_{lpt}(\omega) \right] \right] \right\} - \sum_{l \in L} A_l x_l \tag{50}$$

subject to

$$\sum_{l \in L_p^1} x_l \ge 1 \qquad p \in P \tag{51}$$

$$\sum_{l \in L_p^2} x_l \ge 2 \qquad p \in P \tag{52}$$

and to constraints (9)-(11) and (20)-(24).

It also leads to the transformation of model **M2** into the following model (**M2-R3**):

$$\hat{R}_{\text{M2-R3}} = \max \frac{|T^u|}{|\hat{T}|} \sum_{S=1,H} \frac{\hat{\pi}_S}{m_S} \left\{ \sum_{\omega \in \Omega^{m_S}} \sum_{t \in \hat{T}} \left[\sum_{l \in L} \left(\sum_{p \in P_t(\omega) \cap P_l} \left[\left(u_p - v_l - \hat{w}_{lp} \right) d_{pt}(\omega) \right] x_{lpt}(\omega) - c_l^z z_{lt}(\omega) \right) \right. \right.$$
$$\left. \left. + \left(u_p - \bar{v}^e \right) \sum_{p \in P_t(\omega)} d_{pt}(\omega) e_{pt}(\omega) \right] \right\} - \sum_{l \in L} A_l x_l \tag{53}$$

subject to constraints (9)-(11), (26)-(31) and (51)-(52).

These models are easier to solve than the previous ones. The instruction they provide to the response level is $l(p) = l \mid x_{lp} = 1$. $l'(p)$ is not specified and the default backup policy is used.

5. SN Design Models Solution and Evaluation Approach

The approach used to solve the SAA models formulated previously, and to evaluate their performance in terms of value creation and robustness, is based on the SN design methodology proposed by Klibi and Martel (2009). As illustrated in **Figure 9**, the approach involves three phases: scenarios generation, design generation and design evaluation. It can be seen as an extension of the SAA method used to solve stochastic programs (Shapiro, 2003). The scenario generation is done using procedure **MonteCarlo** presented in **Figure 4**, and it provides scenarios to the design generation and evaluation phases. A large sample of scenarios Ω^{M} is generated and partitioned into low-hazard scenarios Ω^{M_L} and high-hazard scenarios Ω^{M_H}, based on the hazard tolerance level κ. From these samples, two subsets of scenarios are randomly selected to perform the designs evaluation: a subset $\Omega^{M'_L} \subset \Omega^{M_L}$ of M^e_L low-hazard scenarios, and a subset $\Omega^{M'_H} \subset \Omega^{M_H}$ of M^e_H high-hazard scenarios. A subset $\Omega^{M'_W} \subset \Omega^{M_H}$ of M^e_W worst-case scenarios is also selected in the tail of the distribution of the number of hits (**Figure 5**).

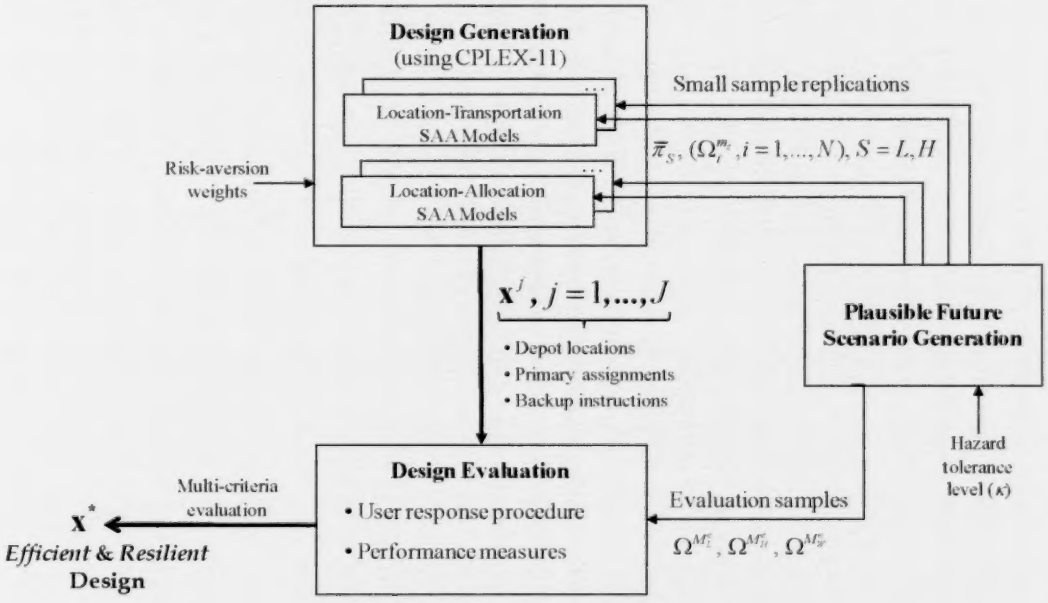

Figure 9- SN Design Models Solution and Evaluation Approach

The design generation phase involves the solution of the SAA models. As normally done with the SAA method, each model is used to generate several designs using N replications of small scenario samples. To do this, another large sample of scenarios $\Omega^{M'}$ is independently gen-

erated and partitioned into low and high hazard subsets $\Omega^{M'_L}$ and $\Omega^{M'_H}$. From these samples, the probabilities $\bar{\pi}_L$ and $\bar{\pi}_H$ are estimated, and N replications of small scenario samples $\Omega_i^{m_L}$, $\Omega_i^{m_H}$, $i = 1,...,N$, are randomly selected to construct the SAA models. Based on $\bar{\pi}_L$ and $\bar{\pi}_H$ the risk aversion weights $\hat{\pi}_L$ and $\hat{\pi}_H$ are also specified. The MIPs obtained are then solved for each sample replication, using a commercial solver such as CPLEX-11 or a specialized solution algorithm. Given the different models proposed and the N replications made, the design generation phase produces a set of alternative SN designs $\mathbf{x}^j$, $j = 1,...,J$. Each SN design obtained specifies the set of depots $\underline{L}$ to open and their primary mission $l(p), p \in P$. For some models, an instruction $l'(p), p \in P$, on the backup depot to use is also provided. When no backup depot is specified, the default reassignment policy applies.

In the evaluation phase, the alternative designs $\mathbf{x}^j$, $j = 1,...,J$ are compared using the plausible future scenario sample $\Omega^{M^e} = \Omega^{M_L^e} \cup \Omega^{M_H^e} \cup \Omega^{M_W^e}$. Since the models proposed incorporate approximate anticipations of the user response, it is not adequate to use their objective function to determine the best design. Moreover, these objective functions do not cover all the value creation and robustness dimensions that decision-makers may want to explore. For these reasons, the evaluation of the SN designs is based on a set of measures related to the net revenues $\hat{R}^u(\mathbf{x}^j, \omega)$, $\omega \in \Omega^{M^e}$, $j = 1,...,J$, provided by the **UserResponse** procedure. More specifically, for a given design $\mathbf{x}^j$, these performance measures are based on the value added during the planning horizon under the scenarios considered, that is:

$$\hat{R}(\mathbf{x}^j, \omega) = \hat{R}^u(\mathbf{x}^j, \omega) - \sum_{l \in L} A_l(x_l^j), \ \omega \in \Omega^{M^e} \tag{54}$$

An adequate SN design evaluation must be based on expected value and robustness measures, and it must take the decision-makers risk attitude into account. The expected return $\bar{R}(\mathbf{x}^j)$ of a design $\mathbf{x}^j$ is provided by:

$$\bar{R}(\mathbf{x}^j) = \sum_{S=L,H} \bar{\pi}_S \bar{R}_S(\mathbf{x}^j); \qquad \bar{R}_S(\mathbf{x}^j) = \frac{1}{M_S^e} \sum_{\omega \in \Omega^{M_S^e}} \hat{R}(\mathbf{x}^j, \omega), \ S = L,H \tag{55}$$

where $\bar{R}_L(\mathbf{x}^j)$ and $\bar{R}_H(\mathbf{x}^j)$ are conditional expected returns for low and high hazard scenarios, respectively. Robustness is related to the variability of the returns obtained under different scenarios. Since downside deviations from mean returns are undesirable, an adequate variability measure to assess a design $\mathbf{x}^j$ is the mean-semideviation $MSD(\mathbf{x}^j)$ given by:

$$\begin{aligned} MSD(\mathbf{x}^j) &= \sum_{S=L,H} \bar{\pi}_S MSD_S(\mathbf{x}^j) \\ MSD_S(\mathbf{x}^j) &= \frac{1}{M_S^e} \sum_{\omega \in \Omega^{M_S^e}} \max\left[\left(\bar{R}_S(\mathbf{x}^j) - \hat{R}(\mathbf{x}^j, \omega)\right); 0\right], \ S = L,H \end{aligned} \tag{56}$$

where $MSD_L(\mathbf{x}^J)$ and $MSD_H(\mathbf{x}^J)$ are conditional mean-semideviations for low and high hazard scenarios, respectively. The mean-semideviation is a coherent risk measure (Shapiro, 2007). Decision-makers are also interested by the behaviour designs under extreme conditions. Using worst-case scenarios, this is often evaluated with the absolute robustness criteria proposed by Kouvelis and Yu (1997). For design $\mathbf{x}^J$ this measures the minimum return $\overline{R}_W(\mathbf{x}^J)$ under all worst case scenarios, calculated as follows:

$$\overline{R}_W(\mathbf{x}^J) = \min_{\omega \in \Omega^{N'_W}} \left\{ \hat{R}(\mathbf{x}^J, \omega) \right\} \tag{57}$$

Measures (55)-(57) provide the basis for a multi-criteria evaluation of the designs considered. Note that these measures can be used to compare the designs provided by the N replications of a given SAA model, as well as the best designs obtained from the different SAA models.

The previous performance measures can also be used to construct a compound return measure reflecting the decision-makers aversion to variability and to extreme events. Such a measure is provided by the following expression:

$$\mathrm{R} = (1-\psi) \sum_{S=L,H} \hat{\pi}_S \left(\overline{R}_S(\mathbf{x}^J) + \varphi_S MSD_S(\mathbf{x}^J) \right) + \psi \overline{R}_W(\mathbf{x}^J) \tag{58}$$

where $\varphi_S \in [0,1]$, $S = L, H$, are variability aversion weights for low and high hazard scenarios, and where $\psi \in [0,1]$ is an extreme event aversion weight. Note that if we set $\varphi_L = \varphi_H = \psi = 0$, the return function obtained corresponds to the objective function of the SAA models used in the design generation phase.

6. Computational results

This section presents the experiments made to compare the models proposed in the previous sections and it analyse the results obtained. In addition to the eight SAA formulations elaborated, two additional models where included to provide conventional SN design approaches benchmarks. One of them is the deterministic model **M3** which completely neglects uncertainty. The second one is a variant of **M1** neglecting hazards: it's a SAA model considering only the randomness in demand and denoted by **M1-D**. Also, for the eight SAA formulations considering hazards, two types of decision-makers (DM) are considered: a risk neural DM and a risk averse DM. Consequently, in what follows, 18 alternative SN design models are compared.

Plan of experiments

In order to test the SN design models proposed, several problem instances were generated based on the following four dimensions: the SN breadth, the cost structure, the demand characteristics and the depots size. First, two problem instances are considered with different number of potential depots and ship-to points scattered over different geographical areas, as specified in

Table 1. The distances between the network nodes are based on existing road networks and they are calculated with PC*MILER (www.alk.com). A one year planning horizon including $|T^u|$=240 working days is used. A next day delivery service requirement is implemented through a 400 miles limit on the distance between depots and ship-to points. Exceptionally, when the number of incident lanes of a given ship-to-point is less than three, depots with distances larger than 400 miles are also considered.

Problem instance	Geographical Area	Potential depots	Number of ship-to-points
P_1	North-Eastern US States	7	206
P_2	North-Eastern & Midwest US States	15	706

Table 1- Test Problems Instances

Based on the cost structure of a real case, high level fixed costs (a) and low level fixed costs (b) are defined. The fixed cost for each depot A_l is randomly generated in the intervals given in **Table 2**. Also, the unit product value, v_l, are selected randomly in [19,21] and the products price, u_p, are fixed to 23 for all ship-to-points. The values v^h and v^e of the products coming from the external supplier are fixed to 25 and 24, respectively, and the local capacity unit re-course cost c_l^z is fixed to 1 for all the depots.

$[A_l]$; $[v_l]$; u_p	High product value/price
High fixed costs	(a): $[180K, 200K]$;[19,21];23
Low fixed costs	(b): $[60K, 80K]$;[19,21];23

Table 2- Test Problems Cost Structure

To adequately capture the ship-to points demand variability, daily orders are modelled as a compound stationary stochastic process. We assume that the distribution $F_p^q(.)$ of the inter-arrival times is exponential with an expected time between orders η_p. Also a log-normal distribution with a mean μ_p and standard deviation σ_p is used for the order quantity distribution $F_p^o(.)$. Three ship-to-points size (Large, Medium and Small) are defined to generate two types of network: larger ship-to-points networks (*LN*) dominated by large and medium size customers and smaller ship-to-points networks (*SN*) dominated by small customers. The proportion of ship-to-points of different size in each network type is given in **Table 3**. The table also provides the probability distribution parameters used to generate orders for each ship-to-point size. For model **M3** the annual average demand of ship-to-points is given by $\hat{D}_p = |T^u| \mu_p / \eta_p$.

Ship-to-point size:	**Large**	**Medium**	**Small**
Larger ship-to-points Network (LN)	15%	65%	20%
Smaller ship-to-points Network (SN)	10%	30%	60%

μ (cwt)	[480,580]	[300,400]	[120,220]
σ (% μ)	7%	10%	16%
η(days)	[2.5,4.5]	[5.5,15.5]	[20.5,35.5]

Table 3- Ship-to-Point Demand Structure

Finally, problems with large capacity depots (LD) and tight capacity depots (TD) are tested. Each depot l has a capacity level given by $a_l = \upsilon \Sigma_{p \in P} \mu_p / \eta_p$, where υ is a factor randomly generated in the intervals, depending on the network structure, given in **Table 4**. The additional capacity, available for local recourse, is fixed to 25 % of the regular capacity level. Note also that all the vehicles capacity (b^F and $b_k, k \in K$) are fixed to 400 cwt.

Capacity factor υ range	**LN**	**SN**
Tight depots structure (**TD**)	$[0.75;1]$	$[1;1.25]$
Large depots structure (**LD**)	$[1.25;1.5]$	

Table 4- Test Problems Depots Capacity Structure

The combination of these four dimensions yields 16 problem instances. Each instance is denoted as follows: $(i,j,k,l); i \in \{P_1, P_2\}$, $j \in \{a,b\}$, $k \in \{LN, SN\}$, $l \in \{TD, LD\}$.

SAA Models Calibration

The solution and evaluation approach presented in **Figure 9** was implemented in VB.Net 2005, and the experiments reported in this section were performed on a 64-bit server with a 2.5 GHz Intel XEON processor and 16 GB of RAM. All the models were generated with OPL Studio 6.1 and solved with CPLEX-11. This section discusses the calibration of SN design model's parameters, taking into account the solvability of the MIPs obtained. All the design models were solved to optimality with the following CPLEX parameters: *MIP Emphasis* = Optimality, *Aggressive Cuts* strategy, *MIP Relative Tolerance* = 0.005 and *Time Limit* = 10 hours.

Recall that the SAA models are formulated using a subset of $m = m_L + m_H$ scenarios, a subset of planning periods $\hat{T}$, as well as route subsets $\hat{K}_{l\tau}(\omega)$, $l \in L$, $\tau \in T^u$, $\omega \in \Omega^m$, for the location-transportation models based on **M1.** The size of these subsets is therefore an important issue and, clearly, the models become much more difficult to solve as the size increases. Solvability is consequently a major concern, and the subsets were selected as large as possible to remain solvable with CPLEX-11. For all the instances solved, one day per week was sampled in the planning horizon yielding $|\hat{T}| = 48$. For the models based on **M1**, using the set of all routes and a sample of 10 scenarios (with $m_L = m_H = 5$) produced SAA design models that could be solved to optimality for P_1. For P_2, the largest SAA models we were able to solve to optimality were obtained

with 6 scenarios samples (with $m_L = m_H = 3$) using a reduced subset of non-dominated routes. Based on preliminary results, the total number of routes was limited to 1 500 000, including all routes with at most one drop and a subset of interesting routes with at least two drops. Note that since the demand and hazard processes are stationary, and since the planning horizon includes 48 days, for each scenario the user response sub-model is replicated 48 times for demands and hazards generated from the same processes. For this reason, what appears here to be a very small number of scenarios gives reasonable results. Also, for each SAA model, $N = 4$ replications were solved with different scenario samples. These subsets size and replication parameters were used for models **M1**, **M1-R1**, **M1-R2**, **M1-R3** and **M1-D**. The absence of binary route selection variables in the location-allocation SAA models based on **M2** makes them more tractable, and the number of scenarios can be significantly increased to improve the statistical optimality gap. After several preliminary tests on various sample size, m was fixed to 50 for P_1 and to 30 for P_2 (with $m_L = m_H = m/2$). This sample size was applied to models **M2**, **M2-R1**, **M2-R2** and **M2-R3**, with $|\hat{I}| = 48$ and $N = 4$.

Samples of M=1000 scenarios were generated for each problem instance to obtain the smaller design generation and evaluation scenario samples, and to estimate the probability $\bar{\pi}_L$ and $\bar{\pi}_H$ of low and high hazard scenarios. Histograms, for one of these samples for each problem instance, are represented in **Figure 5**. These samples and probabilities were used to calibrate the hazard tolerance level κ and the weight of high-hazards scenarios $\hat{\pi}_H$ for risk averse decision-makers. The values obtained/retained for P_1 and P_2 are given in **Table 5**. The table also provides the weights applied to evaluate the designs with (58), for a risk neutral and a risk averse decision-maker.

	Risk Neutral DM				Risk Averse DM			
	κ	$\bar{\pi}_H$	φ_L and φ_H	ψ	κ	$\hat{\pi}_H$	φ_L and φ_H	ψ
P_1	2	0.28	0	0	2	0.35	0.2	0.2
P_2	3	0.38			3	0.45		

Table 5- Decision-Maker Risk Attitude Parameters

The models based on **M2** and **M3** require transportation cost approximation functions estimated by regression. Using a representative sample of daily routes generated with procedure **UserResponse**, a linear regression function $\hat{w}_{lp} = \hat{\zeta}_0 + \hat{\zeta}_1 m_{lp}$ was estimated for each model type. The regression parameter values obtained for P_1 and P_2 are provided in **Table 6**. In addition, for models **M1-R3** and **M2-R3**, we need to fix a priori the cover-radius to use to define the sets I_p^1 and I_p^2. Several values were tested and the inner and outer radiuses retained for P_1 were 200 and 400 miles respectively. For P_2, the values used were 300 and 400 miles.

	P_1		P_2	
	M2	**M3**	**M2**	**M3**
$\hat{\zeta}_0$	0.1091	0.1009	0.2714	0.1009
$\hat{\zeta}_1$	0.0057	0.0044	0.0058	0.005

Table 6- Regression Parameters by Problem Instance for M2 and M3

The hazard model parameters also needed to be estimated. The US states in the regions covered by problems P_1 and P_2 were used as hazard zones. The exposure levels and the multihazard arrival process for each zone (state) was estimated from historical data on major disasters provided by FEMA (www.fema.gov). We assume that the inter-arrival time distribution $F_z^{\lambda}(.)$ is exponential, and the mean inter-arrival times $\overline{\lambda}_z$ estimated for each state z, from the FEMA data, are provided in **Table 7**. The table also gives the state exposure level $g(z)$ estimated on a scale from 1 to 4. We assume that the impact intensity distribution $F^{\beta}_{g(z)s}(.)$ is Uniform for all z and s. For depots it is expressed in terms of capacity loss with parameters [0,0.25), [0.25,0.5), [0.5,0.75), [0.75,1] for exposure levels g =1,2,3,4, respectively. For ship-to-points it is expressed in terms of demand surge or reductions with amplitude parameters [0,0.1), [0.1,0.2), [0.2,0.3), [0.3,0.4] for exposure levels g =1,2,3,4, respectively. The sign of the amplitude was randomly selected to get 50% surge proportion. For all nodes, the attenuation probability α_n is randomly generated in an interval [0.1,0.2), [0.2,0.3), [0.3,0.4) or [0.4,0.5] depending on the relative area of zone $z(n)$. The impact duration functions (**Figure 2**) used are $\theta_l = 0.007\beta_l^2 + 0.4709\beta_l + \varepsilon_L$ for depots (s_L) and $\theta_p = 0.8419\beta_p + \varepsilon_P$ for ship-to points (s_P). The recovery functions used are similar to the ones illustrated in **Figure 3**, with a stagnation phase of $\lceil 0.25\theta_l \rceil$ periods for depots, and instantaneous deployment and recovery phases and a sustainment phase of θ_p periods for ship-to-points.

State (z)	**VT**	**DE**	**DC**	**MA**	**NY**	**NJ**	**WV**	**KY**	**OH**	**IN**
$\overline{\lambda}_z$ (in days)	537	430	567	578	293	609	391	358	344	466
$g(z)$	4	4	4	4	4	4	4	4	4	3
State (z)	**ME**	**NH**	**RI**	**CT**	**PA**	**VA**	**IL**	**MD**	**WI**	**MI**
$\overline{\lambda}_z$ (in days)	405	577	757	703	355	340	371	607	412	611
$g(z)$	3	3	3	3	3	3	3	2	2	1

Table 7- Multi-Hazard Exposure Levels and Mean Inter-Arrival Times

Numerical Results

Given the 16 problem instances defined previously, this section discusses the solvability of the SN design models proposed, and it studies the quality of the design they provide using performance measures (55)-(58). For each formulation, **Table 8** shows the design models character-

istics for problem instances $(\text{-}, a, LN, TD)$, the mean solution time (MST in seconds) and the solution time standard deviation (STSD in seconds) for P_1 and P_2. Models based on **M1** have a very tight LP relaxation which helps reduce solution times significantly even with the large number of binary variables (> 1 000 000) involved. The solution times are smaller for P_2 than P_1 for **M1-R1** and **M1-R2** because a smaller number of scenarios and routes are used. Even if the models based on **M2** include a mix of binary and continuous variables, their solution times are sometimes longer than for the corresponding **M1**-model because the scenarios sample used is five times larger. The deterministic model **M3** is trivial to solve. Note that there is a lot of variability in solution times from one instance to another. This is explained partly by the fact that CPLEX-11 incorporates a number of heuristics to reduce solution times, and that these heuristics do not work as well on all problem structures and instances.

		M1	M1-R1	M1-R2	M1-R3	M2	M2-R1	M2-R2	M2-R3	M1-D	M3
P1	Variables	1060375	1429062	1269822	1304038	416031	397725	393549	416031	1325259	1453
	Constraints	128811	207914	199431	128006	433030	413690	459742	433442	125708	1658
	MST (s)	786	4696	4448	241	5093	1852	5620	6288	437	< 1
	STSD (s)	1224	8870	4722	127	8259	2099	3201	8057	631	0
P2	Variables	1801570	1952566	1947790	1801570	883766	888542	883766	883766	1796446	10609
	Constraints	276312	444865	443453	277724	906057	906763	905351	907469	271238	11314
	MST (s)	2108	2509	3102	612	1297	939	5200	343	1463	< 1
	STSD (s)	3943	2366	3357	643	1108	1075	3561	209	1283	0

Table 8- Model Characteristics and Average Solution Times for P_1 and P_2

An important issue examined in this paper is the impact of the precision of the user response anticipation incorporated in the design model on the quality of the designs obtained. The location-transportation formulations (**M1**-models) proposed include a relatively precise anticipation, but the location-allocation formulations (**M2**-models) included a more approximate anticipation. Our results show that the two formulations never produce the same design, although in most cases, the location decisions are similar. The difference comes mainly from the assignment of ship-to-points to depots. **M1**-models provide different designs for each scenario sample replications which is to be expected because the sample size is relatively small. **M2**-models often produce at least two similar designs among the four replications solved which, again, is normal since larger scenario samples are used. For the smaller problem P_1, **M2** performs extremely well since it gives the best design half of the time. This is explained by the fact that we were able to use large samples of scenarios in this case (50 scenarios, comparatively to 10 for **M1**-models). However, for P_2, the scenario sample size had to be reduced and **M1**-models almost always perform better than **M2**-models. For some instances, the difference in expected design value reaches 7%. This shows that significant gains may be made by using more precise anticipations and larger scenario samples. A more detailed study of the impact of anticipations in SN design is found in Klibi *et al.* (2009b).

We stressed earlier that our models try to avoid risky depot locations as much as possible. Let $\gamma(\mathbf{x}^j, \omega)$ be the total number of hits on depots under scenario ω when design $\mathbf{x}^j$ is imple-

mented. For a given problem instance, the average number of hits on design $\mathbf{x}^j$ for the scenarios evaluated is given by $\overline{\gamma}(\mathbf{x}^j) = \sum_{\omega \in \Omega^{M^e}} \gamma(\mathbf{x}^j, \omega) \Big/ |\Omega^{M^e}|$. **Table 9** reports the mean of these values by problem type ($\overline{\gamma}_{P_1}(\mathbf{x})$ and $\overline{\gamma}_{P_2}(\mathbf{x})$) for the optimal design provided by each model. The lowest average number of hits is obtained with **M1**, which is congruent with the fact that **M1** is a risk avoidance model. The classical deterministic and stochastic models **M3** and **M1-D** also perform very well from this point of view. This indicates that for the regions of the USA covered by P_1 and P_2, the optimal solutions of **M3** and **M1-D** provide a natural cover against hazards. This would certainly not be the case in general. Note that the designs provided by the resilience-seeking models are hit more often. This is happening, because there is a demand surge for some ship-to-points when they are hit. Resilient networks can then make additional profits by providing a good support to the victims of extreme events. Finally, it can be seen that **M2**-based models yield a higher average number of hits than **M1**-based models.

	M1	**M1-R1**	**M1-R2**	**M1-R3**	**M2**	**M2-R1**	**M2-R2**	**M2-R3**	**M1-D**	**M3**
$\overline{\gamma}_{P_1}(\mathbf{x})$	0.89	1.19	0.90	1.33	1.12	1.31	1.24	1.35	0.90	0.94
$\overline{\gamma}_{P_2}(\mathbf{x})$	1.62	2.19	1.72	2.14	2.18	2.44	2.41	2.44	1.65	1.80

Table 9- Average Number of Depot Hits by Scenario

The behaviour of the designs when hit can be analysed further by examining the average value of a design (calculated from $\hat{R}(\mathbf{x}^j, \omega)$, $\omega \in \Omega^{M^e}$) for scenarios including $\gamma = 0,1,2,...$ hits. **Figure 10** presents a value-hit graph of non-dominated risk-mitigation formulations (**RA**, **R1**, **R2** and **R3**) for $(\text{-}, a, LN, TD)$ problem instances. In terms of value creation under a given number of hits, **RA**, **R1**, **M3** and **M1-D** models are dominated either by **R2** or **R3** formulations. For low-hazard scenarios, **R2**-models tend to give better designs than **R3**-models. However, for high-hazard scenarios, **R3**-models create more value. A similar behaviour is observed for other problem instances. Note however that **RA**-models are often almost as good as **R2**-models.

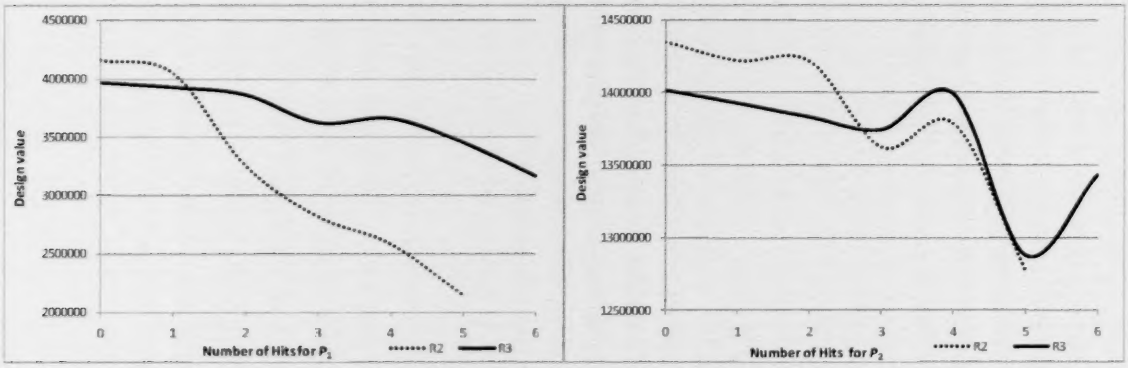

Figure 10- Design Value Behavior by Hit Level for Non-Dominated Models

Robust SN designs should also exhibit low value added mean-semideviations (MSD). **Figure 11** provides value-MSD tradeoffs graphs for P_1 and P_2. The points shown on the graphs for a given risk-mitigation formulation are average values over all the models solved. The graphs show that from a value variability point-of-view, **R1**-models are very conservative: they provide lower value but with lower variability. At the other extreme, **RA**, **R2**, **M3** and **M1-D** models are more aggressive: they provide more value but with more variability. **R3**-models provide a compromise between these two extremes. Note however that the MSD is relatively low, in comparison with expected values, for all models. In other words, for the cases considered, variability does not stand out as discriminating factor.

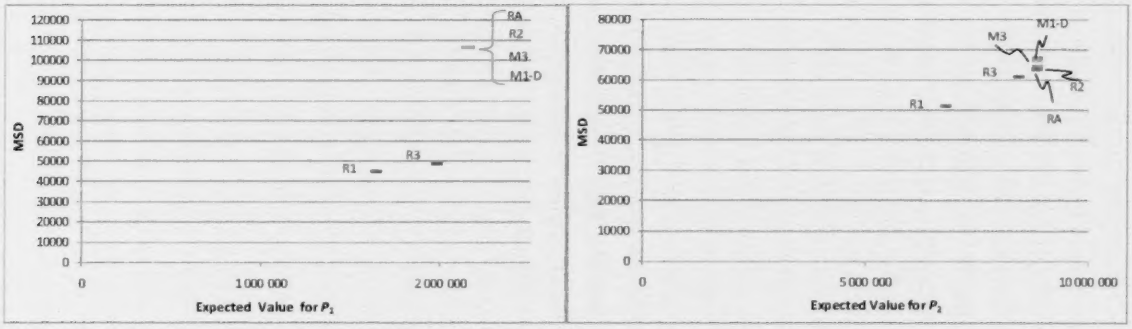

Figure 11- Expected Value – Mean-Semideviation Tradeoffs for P_1 and P_2

All our models were solved with risk-neutral DM weights and risk-averse DM weights (see **Table 5**). **Table 10** presents the percentage of similar design decisions obtained with each risk attitude weights. The table shows that sensitivity to risk attitude depends very much on the model. **R1**-models are much more sensitive to risk attitude than the other models. In general, however, it is clear that the weights selected have an impact on the SN design obtained.

	M1	M1-R1	M1-R2	M1-R3	M2	M2-R1	M2-R2	M2-R3
P_1	69%	0%	56%	44%	63%	0%	41%	59%
P_2	19%	0%	19%	22%	88%	3%	47%	81%

Table 10- Similarity between Design Decisions for DM Types

Table 11 provides more detailed results on the performance of the models for the sixteen problem instances generated. The results are expressed in terms of %-deviation from the return of the best design obtained. When the models are solved with risk-neutral DM weights, the return is evaluated with performance measure (55). When the models are solved with risk-averse DM weights, the results are compared using compound return measure (58), with the weights in **Table 5**. Note that evaluations using higher weights were also made, but it did not have a significant impact on the models ranking. For the SAA models, the table provides the %-deviation of

the best design obtained with the 4 scenario sample replications generated. The best design value for each problem instance is highlighted.

Several observations can be drawn from this table. Note first that the different models never give the same SN design. Model **M1-R2** performs extremely well for larger problems (P_2): it usually provides the best design and, when it does not, it is very close to the best. For smaller problems (P_1), when it is not the best, it is usually dominated by **M2-R2**. This confirms that risk-mitigation formulation **R2** outperforms other formulations. Our results also show clearly that **R1** does not perform very well. Although this risk-mitigation approach is conceptually appealing (Snyder *et al.*, 2006), it is too conservative and it provides poor returns. Since **R3** tends to open more depots, it does not provide the best expected returns but, as shown in **Figure 10**, it may remain attractive to decision-makers wishing to obtain reasonable returns under high disruptions, mainly when depots fixed costs are low.

P_1	*a.LN.TD*	*a.LN.LD*	*b.LN.TD*	*b.LN.LD*	*a.SN.TD*	*a.SN.LD*	*b.SN.TD*	*b.SN.LD*	**All**
Expected Return ($\overline{R}$) for Risk Neutral Models									
M1	-2,25%	-0,94%	-1,06%	-1,87%	-0,30%	-0,68%	-1,10%	-0,17%	-0,38%
M1-R1	-12,66%	-21,74%	-8,14%	-8,30%	-20,16%	-24,84%	-11,31%	-12,04%	-12,86%
M1-R2	0,00%	-0,94%	-1,42%	-1,90%	-0,14%	-0,72%	0,00%	0,00%	0,00%
M1-R3	-4,51%	-4,47%	-3,21%	-0,56%	-8,72%	-9,35%	-4,73%	-2,74%	-3,25%
M2	-2,69%	0,00%	-3,05%	-1,86%	-2,07%	0,00%	-4,39%	-3,88%	-1,43%
M2-R1	-15,61%	-14,29%	-8,68%	-8,67%	-19,95%	-30,23%	-19,48%	-19,57%	-14,27%
M2-R2	-1,39%	-1,07%	0,00%	0,00%	0,00%	-0,48%	-2,29%	-2,89%	-0,05%
M2-R3	-4,43%	-3,26%	-2,92%	-1,86%	-8,57%	-8,37%	-4,63%	-3,88%	-3,27%
M1-D	-4,25%	-1,05%	-0,92%	-1,89%	-2,44%	-0,82%	-0,96%	-0,53%	-0,85%
M3	-4,31%	-1,91%	-0,96%	-1,87%	-2,74%	-0,73%	-0,30%	-0,47%	-0,93%
Compound Return Measure (□) for Risk Averse Models									
M1	-2,18%	-4,25%	-0,18%	-5,47%	-3,08%	-4,86%	-1,31%	-0,23%	-2,04%
M1-R1	-11,69%	-24,77%	-8,41%	-7,71%	-15,65%	-24,39%	-11,33%	-14,23%	-13,02%
M1-R2	0,00%	-4,25%	0,00%	-5,51%	-0,13%	-4,89%	0,00%	0,00%	-1,33%
M1-R3	-6,17%	-6,26%	-4,24%	-3,52%	-11,10%	-12,54%	-4,97%	-3,47%	-5,14%
M2	-3,62%	-3,05%	-2,07%	-2,42%	-3,12%	-1,83%	-4,41%	-4,93%	-2,36%
M2-R1	-11,24%	-11,20%	-8,30%	-9,67%	-21,01%	-30,96%	-15,85%	-15,10%	-12,80%
M2-R2	-1,26%	0,00%	-0,17%	0,00%	0,00%	0,00%	-2,09%	-3,12%	0,00%
M2-R3	-6,04%	-3,26%	-2,15%	-3,57%	-10,73%	-9,25%	-6,23%	-4,93%	-4,29%
M1-D	-10,85%	-4,36%	-0,19%	-5,50%	-9,35%	-5,04%	-0,97%	-0,85%	-3,82%
M3	-10,96%	-4,26%	-0,24%	-5,47%	-9,79%	-4,92%	-0,33%	-0,76%	-3,78%

P_2	*a.LN.TD*	*a.LN.LD*	*b.LN.TD*	*b.LN.LD*	*a.SN.TD*	*a.SN.LD*	*b.SN.TD*	*b.SN.LD*	**All**
Expected Return ($\overline{R}$) for Risk Neutral Models									
M1	-0,12%	-0,09%	-0,28%	0,00%	-0,70%	-0,11%	-0,36%	-0,04%	-0,10%
M1-R1	-19,35%	-21,40%	-14,55%	-14,91%	-25,78%	-23,14%	-19,12%	-17,44%	-18,73%
M1-R2	0,00%	0,00%	-0,37%	-0,14%	0,00%	0,00%	0,00%	0,00%	0,00%
M1-R3	-2,22%	-2,03%	0,00%	-0,60%	-6,33%	-4,76%	-1,76%	-0,70%	-1,85%
M2	-2,39%	-1,90%	-0,70%	-1,20%	-2,05%	-0,14%	-1,74%	-0,51%	-1,27%
M2-R1	-25,19%	-25,58%	-19,92%	-18,31%	-28,56%	-25,52%	-26,97%	-23,22%	-23,44%
M2-R2	-1,93%	-1,83%	-0,70%	-1,19%	-7,09%	-4,27%	-1,65%	-1,11%	-2,05%
M2-R3	-3,61%	-3,04%	-0,67%	-1,19%	-7,69%	-4,73%	-2,01%	-0,94%	-2,58%
M1-D	-0,20%	-0,08%	-0,23%	-0,03%	-0,68%	-0,07%	-0,87%	-0,03%	-0,15%
M3	-0,82%	-0,08%	-0,27%	-0,62%	-1,95%	-0,08%	-1,41%	-0,33%	-0,54%
Compound Return Measure (□) for Risk Averse Models									
M1	-0,16%	-0,43%	-0,69%	-0,15%	0,00%	-0,18%	-0,47%	-0,18%	-0,18%
M1-R1	-17,42%	-20,76%	-14,74%	-13,13%	-25,70%	-26,00%	-16,79%	-18,47%	-18,18%
M1-R2	0,00%	0,00%	-0,41%	0,00%	-0,68%	0,00%	0,00%	0,00%	0,00%
M1-R3	-1,87%	-2,20%	0,00%	-0,74%	-5,23%	-4,71%	-1,50%	-0,84%	-1,69%
M2	-1,48%	-2,10%	-0,85%	-1,21%	-0,87%	-0,09%	-2,18%	-0,62%	-1,10%
M2-R1	-25,03%	-25,70%	-19,37%	-17,89%	-26,59%	-24,09%	-24,05%	-22,86%	-22,62%
M2-R2	-0,63%	-2,00%	-0,90%	-1,21%	-6,12%	-3,55%	-2,06%	-0,62%	-1,73%
M2-R3	-2,29%	-3,34%	-0,64%	-1,21%	-6,56%	-4,52%	-2,31%	-1,06%	-2,31%
M1-D	-0,31%	-0,40%	-0,60%	-0,19%	-0,69%	-0,12%	-1,72%	-0,17%	-0,36%
M3	-0,72%	-0,38%	-0,60%	-1,01%	-2,57%	-0,10%	-2,24%	-0,54%	-0,80%

Table 11- Models Performance in Terms of Deviation from the Best Design

For P_2, the risk-avoidance model **M1** gives the best result for two problem instances, and it is generally not too far from the best model. Models **M1-D** and **M3** are dominated, but they also provide surprisingly good results for models not considering hazards explicitly. This can be explained as follows. First, in our evaluation process, we use a default depot reassignment policy based on a proximity rule. It turns out that this response policy is excellent and that it copes well with hazards even for designs not optimized for resilience. Second, our results show that the de-

signs obtained are very sensitive to the problem size and topology (P_1 vs P_2). For some problem topology, the designs provided by models not seeking resilience explicitly (**M1**, **M2**, **M1-D** and **M3**), are naturally resilient. Note finally that, except for **R3**-formulations which are sensitive to cost structure, the other models are relatively insensitive to cost structure, customer size and depot size.

7. Conclusions

This paper studies a SN design approach under uncertainty. In the context of the multi-period location-transportation problem, it proposes design models incorporating resilience-seeking formulations. A generic solution approach is also proposed to produce effective and resilient SN designs. The models formulated are based on approximate anticipations of the response procedure implemented by the SN users. Our results show that the quality of the user response anticipation incorporated in a design model is a critical issue: significant gains can be made by using more precise representations of delivery decisions (routes vs flows) and larger scenario samples. Given the computational power currently available, tradeoffs are however necessary. The best approach seems to be to seek an adequate equilibrium between all the dimensions involved (ex: route set cardinality vs scenario sample size) instead of neglecting some dimensions (ex: using a deterministic model to be able to incorporate more routes).

Our results also show that more robust designs are obtained by modeling hazards explicitly. This is particularly important when additional revenues can be generated by providing the demand surge goods required by customers under extreme events. The models proposed to cope with hazards try to avoid risk and to provide resilient network structures. However, the incorporation of resilience-seeking constructs in the design models may induces biases that are not necessarily congruent with decision-makers objectives, mainly when the user response procedures are only roughly anticipated. The **R1**-models proposed to select backup depots are good examples of this phenomenon. This also stresses the importance of evaluating potential SN designs with response procedures that are as close as possible to those used by the company considered. By doing this, we found that a good approach to design effective and robust SN is given by **R2**-models which assume that customers can be served from multiple depots. These models provide resilient networks, even when the user operates under a single-sourcing policy. For decision-makers averse to disruptions, the **R3**-models provide an interesting alternative, particularly when the depots fixed costs are low. In some context, models simply trying to avoid risks (**M1** and **M2**) are also a good alternative.

This paper sheds some light on some important SN design issues, but it also raises several questions to address in future research. Our analysis was based on a single product two-echelon location-transportation problem centered on location decisions at the design level and transporta-

tion decisions at the user level. More complex multi-product multi-echelon problems incorporating sourcing, capacity and market selection decisions at the design level, as well as inventory and production decisions at the user level, should be studied. Also, our experiments were based on two realistic SN with similar topologies in the north-east of the USA. Experiments should be made with more varied network topologies and multihazard processes in different parts of the world. Also, other modeling approaches to get resilient networks can certainly be investigated. Finally, as the design problems considered become more complex, the models formulated become more difficult to solve. This raises the need for the elaboration of heuristic methods to solve the problems, and the issue of the tradeoffs between the models precision and solvability.

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